Serving the Poor Differently: The Effects of Private and Public Schools on Children's Academic Achievement in Basic Education in Mexico

Serving the Poor Differently: The Effects of Private and Public Schools on Children's Academic Achievement in Basic Education in Mexico

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To Luzma, the love of my life,
with whom I have explored so many worlds…
let us explore many more.

To Julieta, fruit of our love and hope,
for bringing light and unimaginable sense to my life.

To my parents,
who have taught me about the importance
of education since earlier than I can remember.

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Abstract

Private elementary schools in Mexico are usually seen by wealthy and middle-class families as an alternative to public education. However, private schools have not been seen until very recently as an academic alternative for the poor. In my dissertation, I used data on students from poor families (beneficiaries of *Oportunidades* program) attending sixth grade of elementary school, who participated in the *Quality and Educational Achievement Test assessment* 2009 (EXCALE06-2009), to evaluate if there is a private school advantage for the poor in Mathematics in Mexico. I also investigated the extent to what achievement differential is explained by important features of private schools, such as physical resources, school management, teacher quality, teaching practices and classroom organization, and peer group composition. I used propensity score-matching to correct for bias arising from the self-sorting of students into type of schools.

I concluded that private schools in Mexico offer a clear advantage for poor students in elementary education, even after accounting for selection bias. On average, private school students who are beneficiaries of *Oportunidades* program outperformed their public counterparts by 48 test points in Mathematics, or 48% of a standard deviation. The results passed different robustness checks and are technically reliable.

The 0.48 sd effect size of private school is larger relative to much of the existing literature, especially if it is compared to the results of true experiments or quasi-experiments of private schools conducted in the U.S. I hypothesize that these large results might have to do in part with two factors: the use of the right counterfactual for this research: poor students attending private urban schools; and the fact that students in the

sample attending private schools are all beneficiaries of *Oportunidades*, a comprehensive poverty alleviation program. This might mean that the treatment under study is more complex than just private schooling.

After statistically accounting for selection bias, all of the remaining private school effect is accounted for by identifiable school factors. Peer group composition, school management, teacher practices and classroom organization, are the most important factors explaining the private school advantage in Mathematics in elementary schools in Mexico.

Introduction

Private elementary and lower-secondary schools are usually seen as an alternative to public education for wealthy and middle-class families. However, in many developing countries, private schools serve an increasing number of middle-class and poor students (Akaguri, 2013; Alderman, Kim, & Orazem, 2003; Angrist, Bettinger, Bloom, King, & Kremer, 2002; Psacharopoulos, Arieira, & Mattson, 1997; Tooley & Dixon, 2007; Uribe, Murnane, Willett, & Somers, 2006; Wolff & de Moura Castro, 2002). In Mexico, for instance, affordable private schools are starting to help meet the excess demand for elementary and lower-secondary education and, in the process, releasing pressure on an overflowing public educational system (Bracho & Zamudio, 1998; Velez Bustillo, 2001). Also, with Mexico's primary public schools[1] -- especially those attended by the poor -- facing problems of inadequate resources (Treviño & Treviño, 2004), prolonged teacher strikes, and low scores for their students on standardized tests (INEE, 2006) -- it should not come as a surprise that middle-class and poor parents who are seeking educational quality are starting to enroll their children in affordable elementary private schools.

It is often simply *assumed* that private schools are more effective than their public school counterparts in enhancing their students' academic achievement (see Somers et al.,(2001) to see some examples). However, there is no sound empirical evidence, as yet, that this assumption holds for the affordable private schools that are now being chosen by the poor in Mexico, and whose performance I will examine in this thesis, nor is there any indication as to what the determinants of any differential in student achievement, by sector, might be. In addition to investigating differences in student academic

[1] In Mexico, basic education is mandatory and comprises elementary education (grades 1 through 6) and lower-secondary education (grades 7 through 9).
[2] A theoretical economic framework that explains the size of the private education sector across countries can be found in Estelle James (1987, 1993). Also, see Somers et al. (2001) for an application of the same framework to the Latin American context.

performance between the public and private sectors in Mexico, at the elementary level, I also investigate how any achievement differential that I detect differs by important features of the educational system in Mexico, including physical resources, school management, teacher quality, and teaching practices and classroom organization, as best as the available proxies for those constructs allow. I am also analyzing the role that the student's peer group has on the private school achievement differential, a recurrent explanatory factor of educational achievement. In my research, I use data on primary students from poor families, who participated in the *Quality and Educational Achievement Test assessment* (EXCALE) conducted by the *National Institute for Educational Evaluation* (INEE), during the academic year 2009-2010. Excale is a school survey and assessment administered to a nationally representative stratified random sample of schools, in which students are given a curriculum based test in the subjects of Mathematics, Spanish, Natural Sciences and Civic Education, and a self-administered questionnaire that covers household information, and student's perception about different factors that include characteristics of the instruction they experience, and home background. Teachers and school principals are also given surveys, which covers different aspects of the school life and characteristics that go from school physical and educational resources to teacher and principal practices. My research is *observational*, rather than *experimental* (in which children are randomized to private and public schools) and so, I am using propensity score-matching to assess the sensitivity of my findings to selection bias (Rosenbaum & Rubin, 1983).

The analysis that I will present and discuss in this study shows that there is indeed a private school advantage for the poor in Mexico in mathematics, even after accounting for selection bias. I also show that after statistically accounting for the effect of achievement of peer group composition, the remaining achievement differential can be explained by school factors, such as physical resources, school management, teacher quality, and teaching practices and classroom organization.

1. Comparing Student Achievement in Public and Private Schools

1.1. Background On Private Education and The Poor In Mexico

Ten years ago, there was an increase in the supply of private education in Mexico, as measured by the total number of private schools and by the share of total enrollment that attends private schools. At the elementary education level (grades 1 through 6), the proportion of the total student enrollment educated in private schools in Mexico rose from 6.2% in 1996 to 8.1% in 2004. At the lower-secondary level (grades 9 through 12), private enrollment reached a peak of 13.8% of total student enrollment in 2001, and then leveled out at 12.6%. According to the 1999 Economic Census of the National Institute of Statistics and Geography (INEGI, for its acronym in Spanish), the number of private establishments dedicated to educational services grew by 34% from 1999 to 2009 (de la Calle & Rubio, 2012). However, the most reliable data to really appreciate the size of the private education center comes from Census of Schools, Teachers, Students of Basic and Especial Education 2014 (CEMABE for its acronym in Spanish). This is the first physical census conducted in Mexico to really count the number of schools, teachers and students in basic and especial education in the country. Table 1 presents the number and percentage of public and private schools at different educational levels.

Table 1: Number and percentage of public and private schools in Mexico, broken down by educational level

	Public Schools		Private Schools		
Educational Level	No.	%	Private	%	Total
Preschool	48,620	77%	14,737	23%	63,357
Primary Education	68,544	89%	8,668	11%	77,212
Lower-Secondary	27,020	85%	4,717	15%	31,737
TOTAL	144,184	84%	28,122	16%	172,306

Source: statistics computed by the author based on information from the CEMABE 2014 (database retrieved from: http://imco.org.mx/banner_es/datos-publicos-del-censo-educativo/ on October 1, 2014)

According to the CEMABE 2014 data, 11% of primary schools are private. Previous statistics from the educational sector -- computed based on number of students and not number of schools – indicated that the percentage of students in private primary schools had never been higher than 8.1%. However, this does not necessarily suggest that the private educational sector grew in any way after the last peak registered ten years ago. Private schools are, on average, smaller than public schools. Therefore, it is completely possible that private schools account for only 8.1 percent of the enrollment, but account for 11 percent of total number of schools. Educational authorities are going to release the statistics of student enrollment of the CEMABE 2014 in the next months, which would give us the opportunity to see if the private education sector has grown in term of actual student enrolment and not only in terms on the number of schools.

Traditionally, private education has been an option only for wealthy or middle-class families that can afford to pay tuition fees. However, there are some recent indications that families with more precarious economic conditions, and even the poor, have begun to participate in this modality of education. For example, Bracho and Zamudio (1998) analyzed survey data on household income and expenditure administered by the Mexican Government in 1992, and reported that, out of the total number of families that admit having children in elementary private schools, 10.1% belong in the three lowest income deciles.

The availability of private schools for families from very different economic status in Mexico, resembles the educational supply conditions observed in other developing countries, such as Bolivia (Psacharopoulos et al., 1997), Chile and Haiti (Wolff & de Moura Castro, 2002), Colombia (Angrist, Bettinger, Bloom, King, & Kremer, 2002) Ghana (Akaguri, 2013), India (Tooley & Dixon, 2007), Nigeria (Tooley, 2005), and Pakistan (Alderman et al., 2003). In some cases, the increase in private school demand has been driven by an insufficient supply of public schools and the disenchantment of parents and students with respect to public school quality. The fact that in some countries, like Ghana (Akaguri, 2013) and Mexico (Treviño, 2005), public education is not really free –it usually entails direct and indirect expenditures such as uniforms and the payment of school imposed fees- makes low-fee private schools attractive to some poor families, since they seem to represent a more effective substitution for public schools. In other cases, the increase has been driven by government policies (James, 1993).

Since there is no empirical evidence examining the determinants and predictors of the demand for basic private education in Mexico, it is not known why the poor are interested in the private educational sector. Research on this topic from other Latin American countries suggests that the poor may be opting for private education for their children because of important characteristics of the school market place[2]. For example, one hypothesis is that insufficient provision of public education in the region may be responsible for increasing the demand for private schools. Or, parents may be turning to private schools because they perceive that the public schools are of poor quality, even if the change places a financial burden on the family.

In Mexico, both hypotheses are plausible. At the elementary education level, the coverage is almost universal across all economic strata; therefore, an increasing demand for private education may be better explained by the poor educational quality of public schools (Treviño & Treviño, 2004). What little concrete empirical evidence exists – that is, qualitative evaluations of *Oportunidades*, a transfer program that provides financial resources to almost all poor families in Mexico, conditional on enrolling their children in school -- provide accounts of poor parents opting for affordable elementary private schools for their children because of their perceptions of the inadequate quality of public schools (Escobar Latapí & González de la Rocha, 2003).

1.2 Is There A Private School Advantage?

The debate of whether there is a private school advantage sparked in 1982, after Coleman, Hoffer and Kilgore presented the results of their analysis using the *High School and Beyond* data (1982) and the latter publication of their final research results (Coleman, Hoffer, & Kilgore, 1982). Their main finding was that private high schools, particularly Catholic high schools, are more effective than public schools in enhancing the cognitive

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[2] A theoretical economic framework that explains the size of the private education sector across countries can be found in Estelle James (1987, 1993). Also, see Somers et al. (2001) for an application of the same framework to the Latin American context.

skills of their students. Also, a key finding of that study is that there were even larger differences in social outcomes between students and private and public high schools.

This conclusion became widely criticized by the research community, especially because the original study did not include any technique to account for the effect of selection bias (Murnane, Newstead, & Olsen, 1985). Researchers reanalyzing the data suggested that the methods used by Coleman and his colleagues were not of the highest technical standards and concluded that their results were not warranted by the evidence (Goldberger & Cain, 1982). Their conclusion was that students at Catholic private schools do not do better or worse than their public school counterparts in the outcomes examined of reading and mathematics (Noell, 1982; Witte, 1992).

The issue is, however, far from concluded. Other studies, using different techniques for accounting for selection bias, have concluded that there is indeed a private school advantage, especially for disadvantage children. After accounting for sample selection bias using different instruments, Evans and Schwab (1995) found that attending a private Catholic high school raises the likelihood of finishing high school or entering college by as much as thirteen percentage points. This is consistent with the results found by Altonji, Elder and Taber (2005) analyzing the same outcomes, although they also analyzed the private school effect on achievement, which had no significant effect. Along the same lines, Sander and Krautmann (1995) found, using a different set of instruments for accounting for selection bias, that sophomores attending a Catholic school are more likely to graduate than sophomore in public schools.

The Catholic private school advantage appears to be larger for minority groups. Neal (1997) found that urban minority students attending Catholic schools increase the probability of high school graduation and college graduation, for those graduating high school. The private school advantage even seems to continue into affecting future wage gains.

Other researchers have analyzed the effect of private education in older adults (Sander, 2000) and the effect of private primary schools (Jepsen, 2003), both with positive results.

The question of whether private schools are more effective than public schools in increasing the achievement of students in Latin America does not have a definitive answer. In addition to existing research on this topic being sparse, variation in the local contexts, the educational systems, the modalities of the schools, and the different populations, make generalization difficult.

A comparison of student performance in public and private schools can be made within two different educational contexts: one in which an educational market prevails, and the other in which the provision of education is mainly public (Gradstein, Justman, & Meier, 2004; James, 1987, 1993). The first context tends to foster policies aimed at facilitating an expansion of the demand and supply of private education, one example being the creation and implementation of programs that provide private-school tuition vouchers (Angrist et al., 2002). Commonly, in this context, after policies are implemented, there are dramatic increases in the demand for private schools by families from the middle and lower socio-economic tiers (McEwan, 2001; Uribe et al., 2006). The second context is characterized by the predominance of the state in the provision of elementary education. In this context, private schools are mostly attended by students from families in the middle and high socio-economic tiers, and the expansion of private education itself is not promoted directly by the state (Gradstein et al., 2004). Private school advantage means something different in contexts where only a very small proportion of the poor attends private schools, compared to contexts where a greater share of them does. The Mexican case fits into the former category, since there are no policies in place aimed at increasing the demand for private education or facilitating the expansion of the private education supply. Therefore, most of the students who attend private schools belong to families of middle to high socioeconomic status[3] (Treviño & Treviño, 2004; Velez Bustillo, 2001). In this system, private schools appear more effective at enhancing the achievement of students (Treviño & Treviño, 2004), even after controlling for possible influences on achievement that may stem from students' exposure to the peer groups of differential quality present in public and private schools (Fernández, 2003). However, one needs to express caution in interpreting these findings as indicating that an education in the private schools is superior, as the populations attending each type of school are highly self-selected and from different socioeconomic backgrounds (INEE, 2006).

In other Latin American countries that do not possess educational market systems, such as Argentina or Brazil, findings for a private school advantage are not conclusive either (Somers et al., 2001). In fact, in these countries, once differences in student characteristics between the public and private sector are controlled, the differential impact of private school on student achievement tends to zero (Somers et al., 2001). On the other hand, researchers have found that students in eighth grade attending private

[3] In these studies, the variables measuring socioeconomic status (SES) are indirect. SES is usually measured by indexes that are composed by variables indicating different levels of physical and economic wellbeing. Unfortunately, none of the large-scale evaluation programs, such as those conducted by the INEE or the Secretary of Education, include direct measures of family income.

school in the Dominican Republic scored higher in mathematics tests than their counterparts in public schools, after controlling for socio-economic status, previous achievement and systematic selection by type of school. This latter finding is confirmed even when the impact of non-elite private schools, like the O-type private schools, which cater in great part to the poor, is examined (Jimenez, Lockheed, Luna, & Paqueo, 1991). In the same line, there are two studies in Colombia that also find a private school advantage. Angrist and his colleagues (2002) evaluated the impact of PACES, a program that randomly grants educational vouchers that partially cover the cost of private secondary school. They found that three years after the granting of a voucher, students who won the voucher and subsequently attended private schools scored an average of 0.2 standard deviations higher on achievement tests. Cox and Jimenez (1991) found that private secondary schools in Colombia do offer an achievement advantage, even after comparing students in observationally equivalent settings.

In some developing countries outside of the Latin American region, researchers have found a trend in the provision of private schooling for the poor (Tooley, 2008). In poor areas of Lagos State, Nigeria, for example, 71 percent of schools were found to be private (Tooley, 2005). Similar expansion of the private educational sector has been seen in other countries, such as Uganda, Tanzania and Malawi (Tooley & Dixon, 2006). There is not, however, conclusive evidence to sustain the statement that private schools are more effective at promoting student achievement than public schools. Despite the fact that in many of these studies there is evidence that private schools expose students to much more teaching activity (Tooley, 2005; Tooley & Dixon, 2007), technical limitations in the studies prevent us from drawing any definitive conclusion about difference in student achievement between public and private schools.

Comparisons of student achievement between public and private schools in countries with voucher-type programs in place have also produced inconclusive findings. The most important case in this category is Chile. In 1980 the military Chilean government introduced a reform aimed at financing public and most private schools with the provision of vouchers. As a result, the educational sectors experienced one of the most rapid and large privatizations of education ever registered. However, after more than three decades after the reform, there is no definitive answer as to whether private schools are more effective at producing academic achievement than public schools (McEwan, 2001; McEwan & Carnoy, 2000). On the one hand, private subsidized non-religious schools appear to provide no real academic advantage over municipally administered public schools. On the other hand, Catholic-voucher schools seem to be somewhat more effective than public schools, but only marginally. In addition to that, the transformation of the education market obtained through the elimination of the government monopoly of education has not brought about the expected results. In fact, the effect of unrestricted choice in Chile has not improved average educational outcomes and it has, instead, lead to increased sorting of students (Hsieh & Urquiola, 2006). Cristian Bellei (2005) reported that five out of ten studies on public-private achievement differential, concluded that subsidized schools score higher than public schools; however, four studies concluded that basically both kinds of schools produce basic similar results; and one study concluded that private subsidized schools score lower than public schools. The author concluded that the studies on the private school advantage are very sensitive to the methodological decisions made by researchers. The research evidence from the only country with full free market of education, does not provide a definitive answer about whether private schools are more effective than public schools.

So far, the comparison between the achievement of public and private school students reviewed in this section has been limited to schools located within the same country. It would be interesting to compare the performance of private and public school students across countries and see if there is any consistent trend of private school students outperforming their public counterparts, even if it is only considering raw achievement. To this purpose, I used the results in mathematics from the latest PISA report (OECD, 2013). I compared the performance of student in the top and lowest quartile of the PISA socioeconomic status across different countries. Under several assumptions (that all students in the top SES quartile attend private schools, all students in the lowest quartiles attend public schools, and that there are no marked differences in the public and private educational market across countries), I identified differences in student achievement in mathematics in private vs. public schools between Mexico and other countries. Mexican students in the top SES quartile (presumably all attending private schools) have an average achievement in math considerably below those students in the lowest SES quartile (presumably all attending public schools) of several countries, such as China, Korea, Canada, Estonia, Ireland, Vietnam, and Poland, among others. This means that even if there is a private school advantage in Mexico, students in Mexican private schools do not outperform students attending public schools in other countries. This information only tells us that the endeavor of studying whether there is a private school advantage, has to be limited to a particular social context to actually have any public policy meaning.

1.3 The Determinants of Private School Advantage

In any given context, finding out whether there is indeed a private-public achievement differential is just half of the story. For policy purposes, we also need to understand what are the determinants of any private school achievement advantage, where it exists (Jimenez et al., 1991). If researchers cannot determine which variables explain a private school advantage, policy makers cannot shape public policy to moderate the differences, and important lessons and opportunities for the educational system will be lost.

Finding out the determinants of school performance had been an academic endeavor that has lasted almost five decades. Ever since the publication in the US of the Coleman Report (Coleman & al, 1966), there has been a big wave of research devoted to understanding the inputs and factors associated to student achievement in the school. However, studies differ in terms of the actual factors that explain achievement. Most of these studies fall under the category of "educational production function". Since the earlier publications, the key objective of educational production function studies is to try to identify the combination of inputs that produces the maximum achievable educational output in the schools (Hanushek, 1979). However, very often researchers chose the inputs they include in their studies based on the availability of data, which usually comes from secondary sources, not guided by educational theory.

Despite all research in the last decades, there is no final agreement as to what are the set of inputs that produce better school outcomes. In fact, earlier reviews of the available educational production function analyses showed that there is no systematic relationship between school inputs and student achievement (Hanushek, 1986). Even resources that have been traditionally associated to student performance, such as promoting teacher training, improving physical facilities or reducing class size, appear to be ineffectively used at school, or, at least, inferior than other policies that concentrate on altering the incentives within schools (Hanushek, 2003).

The longstanding perception of school resources as the answer for school quality seems to be supported by the US educational system data. Between 1960 and 2000, most measures of school inputs rose generously as product of systematic policy changes: pupil-teacher ratio fell by slightly less than 40%, the proportion of teachers with a graduate degree increased by more than 100%, and teacher experience grew constantly. Despite all these changes in the makeup of schools, the performance of students in mathematics and reading in 1999 was only modestly higher than it was in 1970 (Hanushek, 2003).

More recent studies using meta-analytic techniques compiling the results of hundreds of studies seem to differ with respect to the value of inputs in student outcomes found in earlier summaries of the research. Greenwald, Hedges, and Laine (1996) found that resources, such as per pupil expenditure, smaller class size, and teacher education, have a positive effect on student outcomes, and that these effects are large enough to be important for education policy. Hanushek (1996), on the other hand, criticizing the statistical methods and their selection of studies, reiterates that schools use resources inefficiently, making it very difficult to pinpoint resources that systematically makes a significant difference in student achievement.

In a different perspective, it can be argued that student performance on standardized tests might not be the most appropriate measure of school performance. Card and Kruguer (1992) argue that looking at labor market outcomes, such as earnings, might be a more realistic way to evaluate the effectiveness of school. Using differences in school inputs for blacks and whites in the eighteen segregated states from 1915 to 1966, they found that changes in school quality can explain between 50 to 80 percent of the increase in rate of returns to education for blacks workers born between 1940 and 1949.

It is clear that we still have much to learn about what makes school better and how can we measure that improvement.

1.3.1 International perspective and focus of this research

The international literature is far from conclusive on issues of school inputs. For some authors, there are important similarities between research findings about the effectiveness of school resources in the developed world and research findings in developing countries. For example, Hanushek (1995) surveyed more than 100 studies in the developing world and concluded that, like in the US, the relationships between educational inputs and achievement shows that countries pursue very inefficient policies and that inputs have very weak effects on educational outcomes. However, a closer look at this study reveals that the estimated effects of many inputs in the studies covered in the analysis appears positive and statistically significant more often that one would expect it there were no relationship at all between resources and school outcomes. Physical and pedagogical inputs that do not bear much weight on student achievement in the industrialized world, seem to be of some importance in the developing world (Glewwe, Grosh, Jacoby, & Lockheed, 1995). It is very likely that school resources have a differentiated effect in early stages of economic development. In fact, some authors even argue that the poorer the country in economic terms, the more powerful the school effect affected by its resources seems to be. The country's economic situation seems to make an important difference in the way school inputs affect educational outputs (Heyneman & Loxley, 1983; Lockheed & Hanushek, 1988).

Nonetheless, before taking too far positive or negative results about the relationship between inputs and school quality, it is important to keep in mind that international studies are conducted in such diverse settings that it is unwise to extrapolate results found in one country in one particular setting to all countries and settings. The differences of school organizations, institutional arrangement, and labor markets make it very difficult to obtain results applicable to all Latin America.

In my research, I am dealing with poor students attending private schools in Mexico, a setting that has been neglected by the literature. I believe that studies that try to explain the private school advantage by looking at school inputs in schools in general (without focus in any particular population) might not be able to explain the achievement differential of poor students in private and urban public schools in Mexico.

Despite all variables considered in US and international studies, there are some consistent types of inputs used across the literature of school production function (Hanushek, 1995). I am drawing from that literature to choose the four types of school factors that have been hypothesized to explain a public-private achievement differential among students in the international literature, and that are the focus of this study: (a) school physical resources; (b) school management; (c) teacher quality; and (d) teaching practices and classroom organization. For this dissertation, I have selected the four educational factors that have been the target of different educational programs and policy in Mexico in the last two decades (Álvarez, García Moreno, & Patrinos, 2007; Bracho, 2000; Fernández, 2003; Muñoz-Izquierdo & Ahuja, 2000; Reimers, 2006; Schmelkes, 2000; Treviño & Treviño, 2004). There is however one important factor that has been present in the educational production function literature in the US since the very beginning, peer group effects. The importance of peer group composition was highlighted in the Coleman Report (Coleman & al, 1966). Coleman and his colleagues found in their research that if children of poor background, especially minority children, were inserted into schools with students with a better average background, their academic achievement would be higher. These four factors are all susceptible to modification by policy and are, therefore, within the scope of change of politicians and policy makers. I discuss these factors briefly, below.

There is overwhelming evidence that school facilities have an influence on educational achievement across developing countries (Hanushek, 1995). Since most private schools charge tuition fees and have considerable discretion in the allocation of their resources, they may be able to purchase additional physical and educational resources, such as books and computers, to enhance the academic performance of their students. Researchers have shown that school physical characteristics and equipment are important determinants of student performance in Latin America (Cox & Jimenez, 1990; Fernández, 2003; Fuller & Clarke, 1994; Heyneman & Loxley, 1983; Jimenez et al., 1991; Treviño & Treviño, 2004). Physical resources have been present as an important factor in educational research since the Coleman Report (Coleman & al, 1966) and the first analyses on the quality of school conducted afterwards (Summers & Wolfe, 1977).

In addition to physical resources, non-material inputs, such as teaching practices and school management, are very important to school quality. As I pointed out earlier, research tends to show that simply increasing the level of resources does not seem to bring positive student educational outputs. Non-material inputs convey the way physical resources are administered, and represent in general the way the education process is organized (Fuller, 1986). How the schools are managed and led seems to be of much importance for school quality (Fuller, 1986). The way schools are structured and organized form the institutional arrangement that defines the milieu where education takes place. School management has the potential to affect everything that happens at the level of the school. It encompasses issues as different as the way teachers are evaluated, the way the principal promotes collaboration among teachers, or the way they administer their school resources.

With respect to the role of teachers, *teacher* quality and *teaching* quality are two important factors. Measuring directly teacher quality has proven to be a difficult endeavor. Usually, researchers include "teacher education" and "teacher training" as proxies of teacher quality in production function analysis. In the US, these two proxies of teacher quality are rarely related to student performance (Hanushek, 2003). However, "teacher education" and "teacher training" in the developing world seem more relevant than what appears in the US (Fuller, 1986; Fuller & Clarke, 1994; Hanushek, 1995).

Teacher quality seems to be one of the most important real resources of the classroom in private schools (Greenwald, Hedges, & Laine, 1996). Since private schools do not usually exist under the same pressures from teacher unions and regulations that public schools experience, scholars have hypothesized that they have more discretion and resources to hire better-prepared and experienced teachers, which then ultimately impacts the achievement of their students. In Latin America, high levels of teacher education, teacher training, and teacher experience, have proven to be very frequently positively associated with the achievement advantage of students in private schools in the Dominican Republic (Jimenez et al., 1991), Mexico (Treviño & Treviño, 2004), Colombia (Cox & Jimenez, 1990) and other countries (Glewwe et al., 1995).

In addition to the education and training of teachers, it is important to pay attention to what actually happens inside school classrooms. Hanushek suggests that inputs can be classified into two different groups: macro organizational and process characteristics, and what can be considered as micro factors (Hanushek, 1979). The first group comprises factors such as class organization and curriculum. By definition these inputs are relatively easy to identify and are, to a larger extent, reproducible. The micro factors, on the other hand, depend upon the personal skills of the teachers and other individual characteristics and usually take place at the level of the classroom. To this category belong factors such as classroom management and teacher's communication skills. Changes in these factors are harder to implement and ultimately depend upon personal actions. Resources do not operate in a vacuum. It is clear that inputs effects are conditioned on the rules and practices of the classroom (Fuller & Clarke, 1994). The way teaching-learning relationship is constructed inside the classroom is, theoretically, one of the most important factors in student achievement (Fuller & Clarke, 1994). Yet, because of the scarcity of data, very few educational studies in Latin America include these "micro" factors in educational production functions.

The few studies that do include teaching practices as an explanatory factor of student achievement tend to show positive significant results. The length of instruction, for example, is very important to student performance. Research in the US shows that the time allocated to learning is positively associated to reading and mathematics test scores, especially for young children (Brown & Saks, 1986). In the US and Japan, teachers' management of class time (as opposed to only amount of time allocated) is positively associated to higher student's achievement tests (Schaub & Baker, 1991). In the developing world, Heyneman and Loxley (1983) found that hours per work week, hours per day school is open, and number of hours per day in school have a positive statistically significant influence in student achievement in Argentina, Bolivia, Peru, and Mexico. Research in Colombia found that the number of classes offered per year is associated to student achievement in primary schools. In fact, research has shown that private secondary schools in several developing countries tend to have more school days than public schools (Fuller & Clarke, 1994).

Along the same lines, the assignment of homework by teachers also bears weight on student performance, as well as the level of teacher expectations for higher pupil achievement (Treviño, 2004). In Jamaican primary schools, Glewwe and his colleagues (1995) found that pedagogical process are more often related to student achievement in mathematics and reading than physical and pedagogical input variables.

One of the main composite financial indicators of school resources, frequently measured in Latin America, is the student-teacher ratio. However, student-teacher ratio can also be a proxy for teacher-student contact time (Glewwe et al., 1995). In that sense, it can be considered one of the "micro factors" that set the dynamics of the classroom. Angrist and Lavy have shown that in other developed countries such as Israel, class size matters (Angrist & Lavy, 1999). Taking advantage of a rule established by rabbinic scholar Maimonides in the twelfth century, which limited the class size to 40, the authors used a regression discontinuity design to the class-size issue, using the Maimonides rule as an instrument. They found that reducing class size causes significant increase in reading and math test scores in fourth and fifth grade students. A randomized experiment at large scale conducted in the state of Tennessee –the only one of this kind ever conducted in the US- showed that students in smaller classes tend to do better in standardized tests (Finn & Achilles, 1990). In a study aimed at explaining the black-white earning gap between 1960 and 1980, Card and Kruger found that the differential in pupil-teacher ratio between the classes that whites and blacks attended between 1915 and 1966 was associated to a larger black-white wage gap. In Latin America student-teacher ratio is often found to be a statistically significant mediator of the private school advantage (Cox & Jimenez, 1990; Jimenez et al., 1991; Treviño & Treviño, 2004).

Based on the evidence reviewed in this section, I plan to use these four factors to try to explain the private-public advantage.

2. Research Questions

I am investigating whether there is a private school advantage in Mexico, particularly among poor students. As suggested above, I am also examining the extent to which any private school advantage stems from differences in the quality of the schools. My specific research questions are as follows:

1. Are private schools more effective than public school in enhancing the achievement in Mathematics in primary education in Mexico?

2. Does any private-school advantage stem from the higher levels of physical resources, the better school management, the enhanced teacher quality, and the better teaching practices and classroom organization that characterize private schools?

3. Data

I am using the second implementation of the *Exámenes de Calidad y Logro Educativo* (EXCALE06-2009), a testing exercise conducted in Mexico by the *National Institute for Educational Evaluation* (INEE) in June of 2009. EXCALE administered tests of Spanish, Mathematics, Civic Education and Natural Sciences to a representative national sample of students in sixth grade (the last grade in primary school). I am using the Mathematics test and all the associated questionnaires. The test was aligned to the national curriculum for each grade, and was constructed from items calibrated using Item Response Theory (INEE, 2006). The Mathematics test is scored and normalized so it has a mean of 500 points and a standard deviation of 100 points. EXCALE also administered surveys to all students in the sample, and to their teachers and school principals. This dataset is suitable for my research because it not only contains data on student achievement and school choice but also rich information on the student's family and educational background; on teacher education and experience; and on school-level physical resources. It also allows me to determine whether the family has received an *Oportunidades* scholarship.

EXCALE06-2009 comprises 4 databases: one database with the results of the students in Math, and three databases of associated information, one for each of the respondents of each of the three questionnaires (students, school teachers, and school principals). After a series of merges and variable preparations, I constructed a single database containing student data, with their corresponding results on the standardized Math test, their responses to their personal questionnaire, and the answer to the questionnaires administered to their class teacher and to their school principal.

3.1 Sample

I am comparing the academic performance of the population of students from low-income families who attended either a public or a private school. I located a sample from this low-income population within the EXCALE dataset by using information on whether students were awarded an *Oportunidades* scholarship (a yes-answer to the AP035 question in the student questionnaire). In the academic year 2008-2009, about 2.5 million children received an *Oportunidades* scholarship to attend either a public or a private school; that is roughly 18% of the total enrolment of primary education level for that academic year. Because of the limited supply of private schools in rural areas in Mexico, all private schools in the EXCALE database are in urban areas. In fact, it seems that there is barely a private school market for the poor in rural area, despite the fact that in 2009 64% of the population living in rural areas were considered poor. In urban areas, on the other hand, in 2009, 40.4 percent of the population was living under the official line of poverty: 33.7% in poverty and 6.7% in extreme poverty (the figures for rural areas are 38% for poverty and 26.5% of extreme poverty). Therefore, in creating my analytic sample, I included only students from urban public schools, for comparability. In this survey and testing exercise, there are 70,888 students in the 6th grade distributed among 4,299 schools in the sample. EXCALE administered tests for the subject matters of

Spanish, Mathematics, Civic Education, and Natural Sciences. After implementing these constraints, my final sample consists of a total of 3,311 students in 1,524 schools. The sample is distributed as follows: 330 students with *Oportunidades* scholarships distributed in 226 private schools, and 2,981 students with *Oportunidades* in 1,298 urban public schools.

Oportunidades is the flagship social development program of the Mexican government. It is a conditional transfer program; it offers an economic stipend and scholarships in exchange of certain behaviors expected from the beneficiaries, such as attending school, having regular medical check-ups, among others. Families that are covered by the program, who are living under the official poverty line, receive an economic scholarship depending on the age of their children, their educational level, and their gender.

It is very likely that the scholarship awarded to parents through *Oportunidades* is high enough to pay for private education There is no general database comprising the tuition and fees that private schools charge, but according to information from Mexican household survey, where parents report how much they spend on tuition and fees for the private education of their children according to their economic level, poor families invest in private tuition and fees in amounts even below of *Oportunidades* scholarships (G. Treviño, 2005).

Children in the sample, students who are beneficiaries of *Oportunidades*, are different themselves from the rest of the population. Table 2 compares the students in the sample with the rest of the universe from EXCALE06-2009.

Table 2: Comparison of student achievement in Mathematics between students included in the sample (poor students that belong to *Oportunidades* program) and the universe of students in Excale.

	Urban Public Schools			Private School		
	N	Mean	s.d.	N	Mean	s.d.
Universe	8331	520	93	2087	591	99
Sample	2981	493	89	330	572	103
Total	11312	513	92	2417	589	100

Student in the general population outperform their poor peers in the sample in both urban public schools and in private schools. In urban public school students in the general population outperform their peers in the sample by a difference of 27 points, a little more than one quarter of a standard deviation in mathematics test. In private schools that difference is of 19 points only. It is interesting to see how poor students attending private schools perform closer to other non-poor children attending private schools. This could be because there is more similarity between the poor and non-poor students attending private schools, or it could be because private schools tend to close the achievement gap between poor and non-poor students. I expect that this research can shed some light into this topic and have a better understanding of *Oportunidades* children.

The EXCALE06-2009 was construed in a way that is representative at the national level. Students in the sample and in the entire population are scattered across all country. Mexico is marked by economic and educational inequalities. All states in the country can be divided into four regions, depending of the percentage of the population within the state living under the line of poverty (CONEVAL, 2010). Table 3 conveys the distribution of the EXCALE data and the dissertation sample, broken down by poverty region.

Table 3: Distribution of students included in the sample (poor students that belong to *Oportunidades* program) versus the universe of students in Excale, broken down by poverty region.

	Poor (Sample)				Non-Poor (Universe)			
	Urban Public		Private		Urban Public		Private	
Poverty Regions	N	%	N	%	N	%	N	%
Region 1 Between 21% and 34.7% poor	719	24%	101	31%	2691	32%	2546	30%
Region 2 Between 34.8% and 42.9% poor	698	23%	106	32%	2395	29%	2388	28%
Region 3 Between 43% and 54.7% poor	779	26%	85	26%	1732	21%	2440	29%
Region 4 Between 54.8% and 78.5%	785	26%	38	12%	1513	18%	1106	13%
Total	2981	100%	330	100%	8331	100%	8480	100%

Poor students attending public schools (included in the sample) are almost equally distributed across poverty regions. However, there is a larger concentration of poor students attending private schools (63%), living in the least poor regions, Region 1 and 2. This is consistent to what we know about private schools, which had developed mainly in the better-off states of the country. This difference seems to be less accentuated with respect to non-*oportunidades* children. There are 58% of them attending schools in Regions 1 and 2 versus 42% attending schools in Regions 3 and 4. One possible explanation for this discrepancy (more poor children attending private schools in the least poor regions than in the poorest regions) is that it might be the case that private schools in better-off states might tend to be more inclusive than those located in poorer (and perhaps more elitist) states, and therefore, more willing to enroll (through scholarships perhaps) poor children.

4. Is There a Private School Advantage in Mathematics?

This part of the dissertation is devoted to answer my first research question. It is divided in five sections. In the first part (4.1), I describe the analytical methodology used to assess whether there is a private school advantage among poor students in Mexico. I begin this part by presenting a brief review of the literature on experimental design and bias correction (4.1.1), and continue with the discussion of the identification strategy (4.1.2), which uses the propensity score matching methodology to estimate the private school effect in mathematics. In the second part (4.2), I present the descriptive statistics depicting the basic feature of student performance in the sample and their personal and family characteristics. In the third part (4.3), I present the empirical results, and in the fourth section (4.4) I introduce three types of sensitivity analyses to offer robustness checks to the findings presented in the third part. In the last section (4.5) I summarize the answer to the first research question.

4.1 Analytical Methodology

4.1.1 The Problem Of Selection Bias: a literature review

From a methodological standpoint, *experimental* research provides the ideal design for assessing the impact of a private school education on student achievement, as compared to that provided by the public school system. In an experiment, children are assigned randomly to private and public schools by an exogenous agent, say the researcher. Then, student achievement is measured and compared across types of schools. Because of the random assignment of students to schools, all unobserved causes of student achievement – perhaps inequities between the systems in important characteristics of the student and the family (such as student ability and parental education) are averaged across sectors and obtained estimates of the private school advantage are unbiased and can be interpreted causally.

However, such experiments are usually neither feasible nor ethically desirable. Parents are (and should be) involved in important decisions concerning their children's education, and this makes the choice of a school in the public or private sector endogenous, potentially correlated with critical parental and student characteristics, such as socioeconomic status, parental and student motivation, and student ability. In other words, in a non-experimental setting, families sort their children into schools, leading to selection bias in estimates of the private school advantage obtained from observational data.

The endogenous nature of school choice challenges the *identification* of the effect of educational sector on student achievement. If student selection into a public or a private school is based implicitly on non-school variables, such as critical student and family characteristics, and these variables are correlated with student achievement, then traditional estimates of the private school advantage (e.g., an observed difference in student achievement averages between sectors) will be biased. For example, if parents with a better educational background tend to send their children to private school, instead of public, then it is likely that the observed effect of private school on the achievement of their children will be confounded with any effects that their own education brings to bear on their children's achievement, resulting in selection bias.

In the absence of controlled experiments, researchers have tried to resolve the selection bias induced by endogenous school choice by introducing control predictors into their regression models to account for variation in these important non-school characteristics. If all the characteristics that drive school choice and student achievement were explicitly included in the statistical model, then bias would be eliminated. However, even when a wide variety of controls, such as parental education, family income, and student ability, are introduced, there may still arguably be other important characteristics that are correlated with both student achievement and school choice that remain unobserved and are omitted from the model, such as parental motivation, which then results in continued bias.

In the last two decades, the selection bias problem has been addressed in more efficient ways, using two-step statistical corrections (Heckman, 1979) or instrumental variable estimation (Angrist, Imbens, & Rubin, 1996)[4]. In these approaches, the selection process itself – here the parents' choice of the public or private sector for their child's school -- is modeled as a function of predictors hypothesized to describe the process, in a "first-stage". Then a "second stage" model describing the link between the ultimate outcome – student achievement – and school choice is fitted, while simultaneously being corrected for the consequences of the first-stage. In this approach, there must be at least one predictor that predicts selection, but does not impact student achievement directly. This predictor, which forms the basis of an "exclusion restriction", is therefore supposed to be correlated with school choice but not correlated with student achievement. The key to making the bias-correction successful is finding a suitable predictor that satisfies the exclusion restriction.

[4] For a review of selection bias in public-private school comparisons, see Murnane (1984; 1985).

Researchers investigating the public-private student achievement differential in Latin America have applied these selection bias corrections with different levels of success (Somers et al., 2001). Some authors have not dealt explicitly with selection bias beyond the point of controlling for student background variables and peer group effects in their regression models (Fernández, 2003; Treviño & Treviño, 2004). Other researchers have applied the Heckman bias correction, or some variation of it, although their choices of predictors to satisfy the exclusion restrictions have differed. Some researchers have used the socioeconomic characteristics of the students' families as predictors of private school enrollment in the first stage equation (Cox & Jimenez, 1990), others have used levels of private school tuition and fees, (Jimenez et al., 1991), or the supply of private schools, as measured by the number of schools per square kilometer in the student's family neighborhood (McEwan, 2001). In this dissertation, I am employing a more robust and partially non-parametric approach to selectivity bias correction using propensity score-matching methodology (Rosenbaum & Rubin, 1983).

4.1.2 Identification Strategy: Propensity Score Matching

In order to make unbiased claims about the causal impact of private versus public schools on student achievement, it is necessary to successfully correct for bias arising from the self-sorting of students into type of schools. To achieve this, I am using propensity score-matching (Rosenbaum & Rubin, 1983; Rosenbaum & Rubin, 1985a, 1985b), in which I use logistic regression analysis to estimate each student's predicted probability of private school enrolment, from their values of observed student and family characteristics that arguably affect their school choice (Dehejia & Wahba, 2002). Using these estimated propensity scores - the conditional treatment probability of private school entry-- I then match each treated observation (each poor student attending private school), with a control observation (a poor student attending an urban public school) with the closest propensity score within the whole distribution of propensity scores. In other words, I am *pairing* students with similar probabilities to be in a private school. In order to do this, I am using a matching estimation called *nearest neighbor*. This methodology was used with replacement, meaning that each control observation can be matched with more than one treatment observation[5]

This technique ensures that all parameters are estimated – and, hence, all comparisons made –within groups of students with similar *risks* of self-selection into private schools, eliminating in this way the observed bias.

Once the matching has been made through nearest neighborhood technique, the difference between student performance in private and public schools can be obtained by subtracting the difference in achievement between matched private and urban public school students and averaging across the sample.

In this research, SES and other individual-level variables will be used as a way to model selection into private schools; a necessary step towards identifying the effect of private school achievement and the elements that explain it. The characteristics of these variables are going to be explained in the next section.

[5] For more reference on the general characteristics of propensity score matching, see (Caliendo & Kopeinig, 2005; Dehejia & Wahba, 2002; Guo & Fraser, 2010; Rosenbaum & Rubin, 1985b)

4.2 Measures and Descriptive Statistics

4.2.1 Measures

Selection of variables that are going to be used in the logistic model use to predict selection into private school is a very important task in the propensity score methodology. According to the literature (Caliendo & Kopeinig, 2005; Heckman, LaLonde, & Smith, 1999; Rosenbaum & Rubin, 1983; Rosenbaum & Rubin, 1985b; Sianesi, 2004; Smith & Todd, 2005), there are five characteristics that the variables included in the logistic model must have. First, the selection of variable should be based on the knowledge of previous specialized literature and knowledge of the institutional setting (Sianesi, 2004; Smith & Todd, 2005), in this case, self-selection into private school in developing countries. Second, the variables must be independent of treatment conditional on the propensity score, a characteristic known as conditional independence assumption, or CIA (Caliendo & Kopeinig, 2005; Sianesi, 2004). Ideally, variables that influence simultaneously the participation decision (in this case, selection into private school) and the outcome variable (achievement in mathematics) should be included in the model. Third, only variables that are unaffected by participation should be included in the model. To ensure this, only variables that are measured before participation should go into the model (Heckman et al., 1999). And fourth, it is ideal that data from participants and non-participants (public and private school students in this case) come from their same source (Heckman et al., 1999).

The variables selected to be part in the model meet these five characteristics. They all are subject-level variables, which come from the same source, the second implementation of the *Exámenes de Calidad y Logro Educativo* (EXCALE06-2009). The selection of the variables was based in the analysis of the literature of private school education in Mexico and other developing countries, which I reviewed in Section 1 of this dissertation. Also, as will be discussed in the next section, the conditional independence assumption holds after matching. Additionally, all the variables affect both the probability of getting into a private school and academic achievement. On the other hand, none of the variables that are going to be used in the logistic model are affected by enrollment in private education and the values of most of the variable either are obtained prior to enrollment into private or public education or are completely independent of it.

In Table A1, in the Appendix, I provide a complete list of variables that are included in my analyses, along with a description of each one of them. I review them briefly below.

My outcome variable is MATH, which measures student performance on an IRT-scaled test administered by the INEE. Scores range from 200 to 800, with higher scores representing higher student achievement. The standard deviation is 100. I will use a dummy predictor, PRIVATE, to indicate whether the student attends a private or public school.

Based on the relevant literature reviewed in Section 1, I am using several predictors to describe student selection into private or public schools. These include predictors measuring individual student characteristics such as gender and age. I am also including a dichotomous variable indicating whether the student received preschool education, and a vector of dummy variables recording the language spoken at home.

I am also including seven predictors that describe family socioeconomic status. I am measuring parental education with two sets of vectors of dummy variables, one for maternal education and another one for paternal education, measuring educational achievement from “no education at all” to “graduate education”.

In order to measure the availability of educational resources at home, I included a vector of six dummy variables indicating the number of books available at home, ranging from zero to “200 or more”. I also created four dummy variables indicating the kind of health service the family has access to, including the access to private health services.

Finally, I created three dummy variables indicating the availability of computer, car and telephone at home as proxies of the level of family’s material wellbeing and socioeconomic status.

4.2.2 Descriptive Statistics

4.2.2.1 Student Performance

There seems to be important differences between the achievement of poor students in urban public and private schools. Poor students in private school perform considerably better in mathematics than poor students in public schools. The average difference is 79 test points, which represent almost 0.8 of one standard deviation unit.

Gross differences are not enough to sustain that students perform better in private schools. Traditional estimates of the private school advantage (for example, analysis of observed difference in student achievement averages between sectors, like the one I just described) are usually biased. Nonetheless, one might think, considering that all students included in this sample in both, private and public schools are officially poor (official beneficiaries of *Oportunidades* scholarships), that one reasonable approach to prove that there is a private school advantage is to simply compare the average performance in each subject matter between poor students in both types of schools. According to the literature review, SES seems to be one of the best proxies of the quality of educational opportunity that students have at home, and that appears to be related to both, selection into private school and achievement. Therefore, hypothetically, finding statistically significant difference between students in both types of school would answer my first research question.

In fact, the results of a t-test performed to test the null hypothesis that states that there is no difference between the average performance of poor students in public and private schools in Mathematics, show that the difference of 0.79 sd between the performance of poor students in these two types of schools are statistically significant ($t=15.13$, $p< 0.000$).

However, the fact that students in both types of school are poor does not necessarily mean that their school performance can be compared only based in observational data. In a non-experimental setting, families sort their children into schools, leading to selection bias in estimates of the private school advantage obtained from observational data. There might be factors affecting family decision to send their children to private school that are equally related to student performance in school. Therefore, it is likely that the observed effect of private school on the achievement of their children will be confounded with variables involved in the mechanism of school selection.

4.2.2.2 Family and Student Characteristics

In addition to academic achievement, poor students in public and private schools seem to have some similarities and some differences in terms of their personal and family characteristics. Mean value for student characteristics and socioeconomic status variables for students in public and private schools are shown in Table 4.

Students in private and public schools are on average very similar in terms of their age and the language spoken at their home. The average age in public school is 12.4 years versus 12.15 in private school, very close to the official expected age for sixth graders in Mexico, which is 12 years. Spanish is the language predominantly spoken at home: 95% of the students speak it at home in public schools versus 97% of the students in private schools.

In terms of gender composition, public and private schools are practically equal. In both types of schools, female students account for 48% of the sixth grade student body. On average, parents are equally inclined to send male or female children to private schools.

With respect to SES, private school students have higher SES background than public school students. Parents of private school students have on average more education than parents from students in public schools. For example, the vast majority of mothers (60%) in private schools have high school or college education, whereas only 20% percent of mothers in public schools have completed either high school or college. A similar patter can be observed with respect to the education of fathers, although in this case the achievement gap between those parents in private schools achieving either high school or college and those parents in public schools with the same level of education is 33 percentage points, slightly smaller than the gap found among mothers.

Table 4: Mean values and standard deviation for student characteristics and socioeconomic status of poor children in public and private schools (N=3,311).

Variables	Public		Private	
	Mean	**sd**	**Mean**	**sd**
Female	0.48	0.50	0.48	0.50
Age in years	12.45	0.73	12.15	0.48
Preschool	0.89	0.32	0.99	0.11
Language spoken at home				
Spanish	0.95	0.21	0.97	0.16
Indigenous	0.03	0.16	0.01	0.08
Other language	0.02	0.14	0.02	0.14
Mother's Education				
No formal education	0.07	0.26	0.01	0.08
Primary school	0.33	0.47	0.06	0.25
Secondary school	0.38	0.49	0.17	0.37
High school	0.14	0.35	0.22	0.42
College	0.06	0.23	0.38	0.49
Graduate school	0.02	0.14	0.16	0.37
Father's Education				
No Formal education	0.06	0.25	0.02	0.14
Primary school	0.30	0.46	0.06	0.24
Secondary school	0.37	0.48	0.14	0.35
High school	0.17	0.37	0.21	0.41
College	0.07	0.25	0.36	0.48
Graduate school	0.03	0.17	0.21	0.41
Availability of Books at Home				
No books available at home	0.20	0.40	0.03	0.16
Around 10 books	0.31	0.46	0.16	0.37
Around 25 Books	0.19	0.39	0.16	0.37
Around 50 books	0.15	0.36	0.19	0.40
Around 100 books	0.09	0.28	0.25	0.43
Around 200 books	0.07	0.25	0.20	0.40
Health Services Available to the Family				
Family has no access to medical services	0.04	0.20	0.02	0.15
Family goes to popular or public clinic, or to a pharmacy	0.65	0.48	0.24	0.43
Family goes to IMSS, ISSSTE or similar institution	0.27	0.44	0.43	0.50
Family goes to private clinics and private health services	0.04	0.19	0.30	0.46
Computer at home	0.31	0.46	0.85	0.36
Car at home	0.53	0.50	0.90	0.31
Telephone at home	0.54	0.50	0.89	0.32

The out-of-school educational opportunity of poor children in public and private schools are also very different. Almost all children with *Oportunidades* in private schools have had a preschool education (99%), compared with only 89% of children in public schools. Considering the importance of preschool education in primary school performance, this difference in preschool attainment means that, on average, poor children in private schools tend to have a better level of school readiness for primary school education than poor children in public schools.

Despite the fact that children included in this research, whether enrolled in public or private schools, are all poor in the sense that they are beneficiaries of the *Oportunidades* program, there still seem to be some important differences in terms of socioeconomic status and educational opportunities at home between the families of those students attending private schools and those attending urban public schools. Families with children in private schools have on average more books at home: 45% of them have between 100 and 200 books or more available to their children, whereas only 16% of families with children in public schools have this number of books at home. Also, 73% of families with children in private schools have access to good quality public or private health services, whereas only 31% of families with poor children in public schools have access to this kind of services. In addition to that, 85% of families with children in private schools have computers at home and 90% of them have cars, versus only 31% and 53% respectively for families with children in public schools.

The difference in access to good quality health services, availability of goods, such as cars and computers at home, and parental education between families with children in public and private schools suggests that there are still some differences in terms of economic resources and extra school educational opportunities between families with children in different types of school, despite the fact that both types of families are considered poor by *Oportunidades* program standards, and these differences suggest that the students attending private schools are relatively more advantaged. These existence of these differences suggest that a simple comparison of student's gross achievement in public and private schools, even if it is with supposedly equally poor students, it is not appropriate, and that other techniques should be employed to remove, to the extent that is possible with the data available, any possible source of bias due to the endogeneity of school choice.

4.3 Empirical Results

In order to answer my first research question, I first fitted a logistic regression model to predict selection into private school in a first-stage model for students who tested in Mathematics in the Excale evaluation. As I explained in the previous section, I am only using pre-treatment single-level covariates to obtain the estimated probability of selection into private school. I use of the psmatch2 module in Stata to conduct this analysis[6]. Table 5 presents the results.

The results rendered by the model show that there is no statistically significant effect of being female on predicting selection into private school, holding constant all other variables in the model. This is not surprising since there is no apparent difference in gender composition between treatment and control groups.

[6] E. Leuven and B. Sianesi. (2003) "PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing". http://ideas.repec.org/c/boc/bocode/s432001.html.

Table 5: Summary of Logistic Regression Analysis for the Prediction of *Oportunidades* Students' Enrollment into Private School, for Mathematics test taker's in the EXCALE06-2009, Controlling for Background Variables (N=2,954)

Variable	Coef.	Std. Err.	z	P>z	[95% Conf. Interval]	
Female	0.15	0.16	0.99	0.32	-0.15	0.46
Age	-0.49	0.15	-3.25	0.00	-0.78	-0.19
Preschool	1.23	0.55	2.23	0.03	0.15	2.31
Language Spoken at Home						
Indigenous	-0.75	1.08	-0.70	0.49	-2.86	1.36
Other	-0.27	0.50	-0.54	0.59	-1.24	0.70
Mother's Education						
Primary School	0.63	0.78	0.81	0.42	-0.90	2.16
Secondary School	0.79	0.77	1.02	0.31	-0.72	2.30
High School	1.24	0.78	1.59	0.11	-0.28	2.76
College	2.03	0.78	2.60	0.01	0.50	3.56
Graduate School	1.99	0.81	2.46	0.01	0.40	3.57
Father's Education						
Primary School	-0.86	0.54	-1.61	0.11	-1.91	0.19
Secondary School	-0.78	0.51	-1.54	0.12	-1.77	0.21
High School	-0.32	0.51	-0.62	0.54	-1.33	0.69
College	0.35	0.52	0.67	0.50	-0.67	1.37
Graduate School	0.43	0.55	0.79	0.43	-0.64	1.50
Books Available at Home						
Around 10 Books	0.68	0.41	1.66	0.10	-0.12	1.49
Around 25 Books	0.94	0.42	2.25	0.02	0.12	1.75
Around 50 Books	0.81	0.42	1.93	0.05	-0.01	1.62
Around 100 Books	1.35	0.42	3.24	0.00	0.53	2.17
200 or more Books	1.26	0.43	2.95	0.00	0.42	2.09
Access to Health Services						
Access to Popular Clinic or Pharmacy	-0.46	0.47	-0.98	0.33	-1.38	0.46
Access to IMSS, ISSSTE, or similar inst.	-0.13	0.47	-0.27	0.78	-1.05	0.79
Access to Private Clinics	1.10	0.49	2.24	0.03	0.14	2.06
Availability of Computer at Home	0.92	0.21	4.43	0.00	0.51	1.33
Availability of Car at Home	0.61	0.23	2.68	0.01	0.17	1.06
Availability of Telephone at Home	0.53	0.22	2.44	0.02	0.10	0.96
Constant	-0.47	2.17	-0.22	0.83	-4.72	3.79
Log Likelihood			-597.86795			
LR chi2 (26)			749.35			
Prob > chi2			0.0000			
Pseudo R2			0.3853			

On the other hand, having a positive preschool education have a statistically significant difference in selection into private school, which means that families with children with higher level of school reediness are more likely, on average, to attend private schools. Age has a statistically and negative significant effect. This probably means that children have more probabilities to get enrolled into private schools if they are younger than the official entering age for sixth grade. The logistic model shows that the language spoken at home does not seem to affect the decision of attending a private school. The indicator variables for home language are not statistically significant after holding constant all other variables in the model.

With respect to parental education, higher levels of mother's education seem to have, on average, a positive effect on the likelihood of enrolling children into private schools, especially when mothers have higher education and beyond. The same does not seem to apply to father's education. Once the other variables are held constant in the model, the indicator variables for father education are not significant.

The level of educational resources available at home, measured by a dummy system indicating the number of books available at home, has a strong positive and statistically significant effect in the model. This probably means that parents who have more educational resources at home (and are probably more invested in the education of their children) tend to be more likely to enroll their children in private schools than families with less educational resources available at home.

The rest of the variables in the model, which indicate different levels of SES among families that are beneficiaries of the *Oportunidades* program, are statistically significant and have positive effects. This means, that even among families that are considered poor, having a "higher" level of SES increases the chances, on average, of enrolling children into private schools.

Overall, the model is doing a good job predicting enrollment into private school, and the null hypothesis that states that all logistic regression coefficients are equal to zero at the same time can be rejected at the 1% significant level (LR chi2 = 749.35, Prob > chi2 = 0.0000).

Once the conditional predicted probabilities were estimated for each participant in the study (whether the student is in private or public schools) the matching was performed using the nearest-neighbor matching estimator. Results are presented in table 6.

Table 6: Differences in ATT in Mathematics between students with *Oportunidades* scholarship in Public and Private schools, using the nearest neighbor matching estimator (On support: 2,653 public students, 301 private students)

Sample	Private School	Public School	Difference	S.E.	T-stat
Unmatched	573.71	494.34	79.37	5.47	14.50
ATT	573.71	535.47	38.24	12.74	3.00

The first row in the table shows the results for the unmatched samples of students, before the matching process is carried out. Here we see the result presented a bit earlier – a difference of 79 points, or about 0.80 of a standard deviation. The second row of the table, label ATT[7], provides the important comparison of the scores after the matching process. The private school advantage is equal to 38.24 test points, or 38% of a standard deviation. It is clear that poor private school students outperformed, on average, their

[7] ATT (the average treatment effect for the treated) is the effect focus of this research. It conveys the effect in the population for whom private school is intended.

comparable public counterparts in Mathematics by almost half a standard deviation. The difference between the private school advantage reported in the unmatched sample and the private school advantage reported in the ATT is due to the effect of propensity score matching. The ATT shows the public-private school differential after the attempt to remove the selection bias. It is therefore a more reliable estimate of the difference of poor students performance in both types of schools. Even after the implementation of propensity score matching, the private school differential still remains substantial.

The matching procedure is only using the students in the treatment group (private schools) and the control group (public schools) whose propensity scores overlap. This overlapping region is called common support. Table 6 reports the number of students in public and private schools who are in common support.

Before trusting the results, it is necessary to check for balance between the two groups formed by the nearest matching estimator. Table 7 shows a summary of balancing measures for that purpose.

Table 7: Measures of Balance for after performance of nearest neighbor matching for the Identification of Differences in ATT in Mathematics between Students with *Oportunidades* scholarship in Public and Private schools.

Sample	Pseudo R2	LR chi2	p>chi2	MeanBias	MedBias
Raw	0.379	736.61	0.000	49.9	47.5
Matched	0.037	30.44	0.208	6.5	5.2

The first raw (labeled "Raw") shows the balancing statistics for the unmatched sample, while the second raw (labeled "Matched") shows the balancing statistics for the groups after the matching procedure. The LR chi2 has an associated null hypothesis that states that the values of all the variables in the model are jointly balanced between the two groups. Before the matching procedure was implemented, the null hypothesis of LR chi2 for the "raw" sample was rejected (LR chi2 = 736.61, Prob. Chi2 = 0.000), meaning that the variables in the model were not balanced. After the matching was implemented, I cannot reject this null hypothesis (LR chi2 = 30.44, Prob. Chi2 = 0.208), which means that the variables in the model were correctly balanced. In addition to that, the Pseudo R^2 indicates how well the regressors included in the logistic model explain the participation probability. Once the matching is performed, there should not be any systematic differences in the distribution of explanatory variables between both groups, so the pseudo-R^2 should be low (Sianesi, 2004). In this case, it is low, as it would be expected in the case of good match between the two groups. Also, Mean and Median Bias are both low too, confirming the good match between students in both groups.

To further check that both groups are correctly matched based on their propensity values, I am comparing the mean values of all background variables included in the logistic model between the two groups. Table 8 presents this information along the results of t-test for equality of means and other measures of balance. This information further helps assess the quality of the matching obtained through the nearest neighbor estimator.

The summary of t-test results shows that most variables are considered balanced between the groups of students in public and private schools after matching. For almost all variables I cannot reject the t-test associated null hypothesis that states that there is no statistically significant difference between the mean variable values for both private and public school students. The only exception is one of the variables of the "availability of book at home" dummy system (the variable measuring availability 200 or more books). However, the actual difference in the value of this variable does not seem to be very large to be of concern. Besides, the other variables in the dummy system are well balanced between the two groups.

Table 8: Summary of t-test results for personal-level variables and analysis of balance After Propensity Score Matching Estimation has been conducted for the Identification of ATT in Mathematics between Students with *Oportunidades* scholarship in Public and Private schools using nearest neighbor matching.

	Comparison	Mean			%reduct	t-test	
Variable	Matched	Treated	Control	%bias	bias	t	p>t
Female	Unmatched	0.49	0.49	0.4		0.06	0.95
	Matched	0.49	0.45	8.6	-2363.5	1.06	0.29
Age	Unmatched	12.16	12.44	-45.3		-6.53	0.00
	Matched	12.16	12.10	9.4	79.3	1.47	0.14
Preschool	Unmatched	0.99	0.89	40.9		5.31	0.00
	Matched	0.99	0.98	1.4	96.6	0.34	0.74
Language							
Indigenous	Unmatched	0.00	0.02	-16.9		-2.21	0.03
	Matched	0.00	0.00	3.0	82.4	1.00	0.32
Other	Unmatched	0.02	0.02	2.5		0.43	0.67
	Matched	0.02	0.03	-6.9	-172.7	-0.74	0.46
Mother's Education							
Primary School	Unmatched	0.07	0.33	-71.1		-9.71	0.00
	Matched	0.07	0.09	-5.3	92.6	-0.92	0.36
Secondary School	Unmatched	0.16	0.38	-50.8		-7.57	0.00
	Matched	0.16	0.14	4.6	90.9	0.68	0.49
High School	Unmatched	0.22	0.14	20.6		3.64	0.00
	Matched	0.22	0.17	12.2	40.9	1.44	0.15
College	Unmatched	0.39	0.06	87.6		20.59	0.00
	Matched	0.39	0.45	-15.7	82.1	-1.49	0.14
Graduate School	Unmatched	0.16	0.02	49.7		12.67	0.00
	Matched	0.16	0.15	3.6	92.8	0.34	0.74
Father's Education							
Primary School	Unmatched	0.06	0.30	-68.1		-9.22	0.00
	Matched	0.06	0.06	-0.9	98.7	-0.17	0.86
Secondary School	Unmatched	0.14	0.37	-55.2		-8.10	0.00
	Matched	0.14	0.15	-1.6	97.1	-0.23	0.82
High School	Unmatched	0.21	0.17	11.7		2.01	0.05
	Matched	0.21	0.16	12.7	-8.3	1.57	0.12
College	Unmatched	0.37	0.06	78.5		17.68	0.00
	Matched	0.37	0.35	4.3	94.5	0.42	0.67
Graduate School	Unmatched	0.21	0.03	57.1		14.20	0.00
	Matched	0.21	0.22	-5.4	90.6	-0.50	0.62

…Continuation Table 8

Variable	Comparison Matched	Mean Treated	Mean Control	%bias	%reduct bias	t-test t	t-test p>t
Books Available at Home							
Around 10 books	Unmatched	0.16	0.32	-38.3		-5.76	0.00
	Matched	0.16	0.15	1.6	95.8	0.23	0.82
Around 25 books	Unmatched	0.17	0.19	-5.0		-0.80	0.42
	Matched	0.17	0.15	5.2	-4.7	0.67	0.51
Around 50 books	Unmatched	0.19	0.15	12.6		2.17	0.03
	Matched	0.19	0.23	-9.8	22.6	-1.10	0.27
Around 100 books	Unmatched	0.25	0.09	44.2		8.79	0.00
	Matched	0.25	0.30	-12.6	71.4	-1.28	0.20
200 or more books	Unmatched	0.20	0.07	40.3		8.23	0.00
	Matched	0.20	0.14	18.8	53.3	2.06	0.04
Access to Health Services							
Popular Clinic or Pharmacy	Unmatched	0.24	0.66	-92.0		-14.53	0.00
	Matched	0.24	0.28	-8.8	90.4	-1.12	0.27
MSS, ISSSTE, or similar inst.	Unmatched	0.43	0.27	34.7		5.97	0.00
	Matched	0.43	0.44	-0.7	98.0	-0.08	0.94
Private Clinics	Unmatched	0.31	0.04	76.4		19.16	0.00
	Matched	0.31	0.26	12.3	83.9	1.17	0.24
Availability of Computer	Unmatched	0.86	0.32	130.8		19.46	0.00
	Matched	0.86	0.86	-0.8	99.4	-0.12	0.91
Availability of Car	Unmatched	0.90	0.54	87.0		12.21	0.00
	Matched	0.90	0.91	-2.4	97.2	-0.42	0.68
Availability of Telephone	Unmatched	0.89	0.55	81.1		11.54	0.00
	Matched	0.89	0.89	0.0	100.0	0.00	1.00

In addition to that, Table 8 presents the "%standardized bias" indicator for each variable. According to Rosenbaum and Rubin formula (Rosenbaum & Rubin, 1985b), the standardized bias is defined as the difference of sample means in the treated and matched control subsamples as a percentage of the square root of the average of sample variances in the treated and the control groups. This is a type of effect-size measure. A successful matching procedure this indicator should ideally fall below 5% after matching (Caliendo & Kopeinig, 2005). There are a few variables where this condition is not met. For example, the percentage bias of the variable Female is 8.3. There are about four percent more female students in private schools than in public schools after matching. However, this number can be misleading. In the unmatched sample, this difference is negligible. However, after matching, the percentage changed just a little by consequence of matching in the propensity score, which encompasses all variables in the model. Therefore, the matching is doing a good job, so much so that I cannot reject the associated null hypothesis of the t-test. Another similar case is the variable age. The difference in the average percentage between the two groups is negligible. However, the standardized bias still computes a value larger than 5. In this case, the t-test was also rejected. In fact, it is the same case in all the other variables whose standardized bias is larger than 5, with the exception of the dummy variable indicating whether there are more than 200 books or more available at home.

Additionally, Table 8 presents "% reduct bias" figures (Sianesi, 2004), which indicate how much bias was eliminated by matching process. Ordinarily, negative values suggest that the bias increased as a result of matching. That is the case, for example, in the percentage of students who speak other language. The "% reduct bias" value is -172.7. However, this indicator can be misleading. In the cases where there are variables with already very little bias before matching, the matching process might not make any progress in reducing the bias. However, since the bias is small, the "% reduct bias" does not offer much information. This is the case here, where the original difference (unmatched) in the percentage of students speaking other language was of less of one percent. For the most part, the matching brought good balance between the groups, as confirmed for the values of the "% reduct bias" measure, which shows only negative results for variables that were already very much balanced in the unmatched sample. Overall, the matching through nearest neighbor matching is very good.

4.4 Sensitivity Analysis

Propensity score matching is no universal panacea. It corrects only for the biasing effect of the observed covariates. This approach depends for its success on the skill with which I have chosen covariates and have made a case for their inclusion in the modeling of selection. Propensity score matching does not correct for any bias that come from unobserved variables (Rubin, 1997). So, the adjustment for selection bias that I have done through propensity score matching is only effective to the extent that I exclude no relevant covariate from the selection modeling.

To assess the robustness of the matching estimates vis-à-vis observed and unobserved bias, I implemented three kinds of sensitivity checks. First, I performed different kind of matching estimator to see if the results hold across different matching algorithms. Second, I took into account possible sources of bias related to the geographic location of the school. I fitted a multilevel model to take this into account. Third, I calculated the Rosenbaum bounds for the estimated average treatment effects of private school in math to explore robustness of matching estimates in the context of bias arising from unobserved variables.

The sensitivity analyses will address the possibility that bias may alter the inferences I have established about the private school advantage for the poor.

4.4.1 Use of Different Matching Estimators

To test the consistency of the matching results in the context of potential bias from observed variables, I compared the estimates obtained from the nearest neighbor-matching estimator to the results obtained from 10 other matching algorithms. Considering that there is a lack of agreement on which matching algorithm is more appropriate, Becker and Ichino (2002) recommends testing several of them to analyze the sensitivity of the results to different matching schemes.

I performed matching using the following matching algorithms:

1) *Nearest Neighbor Matching with caliper of 0.01*: to avoid matching a treatment case with a control case too far away in terms of its propensity score value, in this matching scheme there is an imposition, or a caliper, on the maximum distance that can be tolerated between any given treatment case and its match. In this case the caliper is 0.01 sd. of the propensity score distribution.
2) *Nearest Neighbor Matching with caliper of 0.01 and common support*: in this case, in addition to the imposition of caliper, all matching is forced within the common support region.
3) *2-Nearest Neighbors Matching*: instead of matching with one single observation, this approach allows to match each private school student with two public school students. It is has the advantage of using more information for the construction of the counterfactual. The inclusion of more cases reduced variance, but might increase bias by including poorer matches.

4) *Radius Matching, Caliper = 0.01*: in this matching scheme all control cases within the caliper (the radius) are selected and averaged to do the matching.
5) *Kernel Matching (epanechnikov) Bandwidth = 0.06*: this is a non-parametric matching estimator that uses all individuals in the control group to construct the counterfactual. It gives each individual different weight in the estimation depending o its distance to the propensity score of the treatment. The further away the control case is from the treatment case, the less weight it receives in the estimation. The choice of bandwidth (sort of a caliper) and the choice of kernel function are important aspects that affect the estimation. All kernel matching are performed in this study using the epanechnikov function. The bandwidth used in this matching scheme is 0.06.
6) *Kernel Matching (epanechnikov) Bandwidth = 0.01*: This case is very similar to the previous match, with the difference that the bandwidth is now narrower and it is set to 0.01.
7) *Kernel Matching (epanechnikov) Bandwidth = .01 and Trim = 10*: In addition to the parameters of the previous matching algorithm, in this case the observations that fall in regions where propensity scores for the non-treated are sparse are discarded, an exercise called “trimming”.
8) *Local Linear Regression Matching (tricube)*: local linear regression uses a more complex method than kernel matching to calculate the fitted value for treatment and control groups. In this case the predicted value falls onto a regression line specifically drawn to each set of values determined by the bandwidth. Local linear matching uses local linear regression to determine each fitted value.

9) *Local Linear Regression Matching (tricube) Bandwidth = .0 and Trim = 10*: In this case, a narrower bandwidth and a trim are also set.

There is no perfect matching estimator, and each one of them present advantages and disadvantages[8]. There is a general trade-off between bias and efficiency (Caliendo & Kopeinig, 2005), especially in small samples (Heckman, Ichimura, & Todd, 1997). The matching methods that favor the quality of the selected matches, such as nearest neighbor and the methods that impose calipers and common support, tend to obtain results that are less biased. However, the avoidance of bad matches reduces the total number of matched cases, which in turn increases the variance of the estimates, reducing in this way the efficiency. The opposite is also true: matching algorithms that tend to include more cases, such a radius matching and 2-nearest-neighbors matching, reduced the variance because of the increase in sample, but do so with a sacrifice in reduction of bias. Therefore, especial attention should be paid to the trade-off involved when selecting the best matching estimator.

Table 9 presents the results of all matching schemes. The first row presents the results from the nearest neighbor matching that I have already applied to estimate the private school advantage. I have included it to facilitate comparisons with the results from the other methods.

[8] For a complete and easy review of matching estimator it advisable to read Caliendo (Caliendo & Kopeinig, 2005). For a more complete presentation of matching estimators illustrated with many examples, see (Guo & Fraser, 2010).

Table 9: Estimated effect of private school on mathematics test scores using different matching methods

Matching Method	Matching Results: Common Support No. Private Students	Matching Results: Common Support No. Public Students	Matching Results: ATT Difference	Matching Results: ATT S.E.	Matching Quality: Pseudo R2	Matching Quality: LR chi2	Matching Quality: p>chi2	Matching Quality: Mean Bias	Matching Quality: Med Bias
Nearest Neighbor Matching	301	2,653	38.24	12.7	0.037	30.4	0.21	6.5	5.2
Nearest Neighbor Matching, Caliper = 0.01	274	2,653	41.90	11.7	0.03	22.8	0.59	6.9	5.4
Nearest Neighbor Matching, Caliper = 0.01 and Common Support	271	2,653	43.46	11.8	0.032	24.1	0.51	7.2	5.5
2-Nearest Neighbors Matching	301	2,653	48.22	10.9	0.024	20.2	0.78	6.0	4.2
Radius Matching, Caliper = 0.01	274	2,653	48.01	8.82	0.01	7.63	1.000	4.0	2.7
Kernel Matching (epanechnikov) Bandwith = 0.06	301	2,653	47.88	9.04	0.012	10.1	0.99	4.5	4.2
Kernel Matching (epanechnikov) Bandwith = 0.01	274	2,653	46.78	8.96	0.011	8.55	1	4.3	2.5
Kernel Matching (epanechnikov) Bandwith = .01 and Trim = 5	274	2,653	46.78	8.96	0.011	8.55	1	4.3	2.5
Kernel Matching (epanechnikov) Bandwith = .01 and Trim = 10	270	2,653	46.32	8.71	0.010	7.60	1.000	4.1	2.5
Local Linear Regression Matching (tricube)	301	2,653	49.78	12.7	0.037	30.4	0.21	6.5	5.2
Local Linear Regression Matching (tricube) Bandwith = .0 and Trim = 10	271	2,653	48.55	11.6	0.029	21.9	0.64	6.8	4.6

The average difference in performance in the standardized mathematics test of poor students in private and public schools across all matching algorithm is 46 point, or 46% of a standard deviation. The private school advantage ranges from 38.2 test points (from the nearest neighbor matching estimator) to 49.8 points (obtained from Local Linear Regression Matching, tricube). That is only a difference of 11.5 points.

The trade-off between quality of matching and increase in variance that characterizes the choice of a matching scheme can be appreciated by looking at the different values of standard errors in Table 9. Some of the smaller standard errors are obtained in matching algorithms that include by design more control cases in the construction of the counterfactual, such as radius matching and kernel matching. On the other hand, the larger standard errors are obtained through matching techniques that privilege the inclusion of higher quality matches –and therefore, the inclusion of a smaller number of control cases- in the construction of the counterfactual, such as nearest neighbor matching and nearest neighbor matching with 0.01 caliper and imposition of common support. In this way, the bias could certainly diminish, although it involves a price in increase in variance.

Despite the differences in values of standard errors, private school advantage is statistically significant in all cases, meaning that the differences among the various algorithms are not large enough to affect the common conclusion drawn from all matching techniques.

In terms of matching quality, all matching algorithms present very similar results. The null hypothesis associated to the LR chi2, which states that the values of all the variables in the model are jointly balanced between the two groups, cannot be rejected in all matching methods with very similar probability values. Also, the Pseudo R2 is considerable low across old methods and the Mean and Median Bias are both consistently low too, confirming the good match between students in both groups in all matching methods.

I also calculated robust standard errors for the matching estimators that allow the performance of bootstrapping. Table 10 presents the results. The results are consistent with the results from other matching estimators.

Table 10: Bootstrapping of standard error for the estimation of the effect of private schooling in Math.

Matching Estimator	Observed Coefficient	Bootstrap S.E.	z	P>z	Normal-based [95% Conf. Interval]	
Kernel Matching (epanechnikov) Bandwith = 0.06	47.885	10.828	4.42	0.000	26.663	69.107
Local Linear Regression Matching (tricube)	49.785	8.791	5.66	0.000	32.554	67.015

The consistency of matching estimates across various types of matching algorithms is an indication of robustness (Morgan & Harding, 2006). The evidence presented in this section proves that my earlier results are robust to sources of bias arising from the observed variables considered in this research.

4.4.2 Contextual Effects

The basis for all matching algorithms used in the last section was the propensity scores obtained through the same logistic regression model. There are, however, two important sources of bias and threats to validity that arises from this model that are important to address: 1) the nested structure of the EXCALE data (student nested within schools, nested within states or regions); and 2) the possible existence of a contextual effect that it has not been properly included in the model. This section is aimed to address these limitations.

According to Thoemmes and West (2010), the propensity score model should consider the clustered nature of the data when it is present, in both, the estimation of the propensity score and in the matching process. Multilevel models are the more appropriate way to accomplish this goal.

Given the distribution of my sample, the cluster level that might be the source of more serious bias is the Mexican states where the student attended either public or private school[9]. States vary significantly with respect to their level of poverty, availability of private and public schools (even in urban cities), and many other possible hidden factors that might affect the probability of a child to get into private school, such as inter-state variation in parental interest in private education, or the quality itself of private schools. Table 11 show the distribution of students in public and private schools, broken down by the 32 Mexican states. There is an important dispersion of students in private and public schools across the whole country. This variation is intentional in the sense that Mexican Government (who conducted the Excale evaluation) wanted to ensure that any result drawn from the original data would be representative for the whole country.

[9] The aggregation of students within schools is being accounted in two different ways. First, the estimation of standard errors in each analysis is taking into account the lack of independence of individual within schools, so the errors are properly estimated regardless of the aggregation of students within school. Second, as part of the analyses conducted to answer the second research question, a whole set of school level variables that might affect student achievement are taken into account in the analyses.

Table 11: Distribution of students in the sample, broken down by type of school and state

State	Urban Public	Private
BAJA CALIFORNIA	67	9
BAJA CALIFORNIA SUR	103	6
CAMPECHE	116	8
CHIAPAS	96	0
CHIHUAHUA	65	9
COAHUILA	100	10
COLIMA	129	9
DISTRITO FEDERAL	60	10
DURANGO	52	9
GUANAJUATO	99	5
GUERRERO	119	0
HIDALGO	71	11
JALISCO	81	12
MEXICO	82	16
MICHOACAN	70	13
MORELOS	123	20
NAYARIT	83	14
NUEVO LEON	44	14
OAXACA	22	0
PUEBLA	101	5
QUERETARO	78	18
QUINTANA ROO	113	15
SAN LUIS POTOSI	88	14
SINALOA	84	15
SONORA	103	28
TABASCO	131	13
TAMAULIPAS	102	13
TLAXCALA	159	11
VERACRUZ	85	0
YUCATAN	160	5
ZACATECAS	72	9

In other words, the number of cases in each state is not related to any particular characteristic of the state. Nonetheless, selection into private schools or achievement itself can be affected by observed or hidden characteristics of each state. I estimated the value of intraclass correlation for understanding the variation of Private (the dummy variable indicating whether the student attends a private school, which is the outcome of the logistic regression) across states. The intraclass correlation value is 50% ($\rho=0.50$), meaning that 50% of the variation of Private is across states.

There are two important considerations to take into account in making the right choice of model and conditioning scheme: one referred to how to model the influence of the variables of interest at each level of the hierarchical model; and the second referred to the appropriate way to do the matching based on the propensity scores (Thoemmes & West, 2010).

An important decision to make is whether the clustering of the data is a central part of the design or if it is rather an incidental feature (Guo & Fraser, 2010; Thoemmes & West, 2010). When it is considered that clustering is a central feature of the design, for example, when a program is going to be evaluated intentionally in two different kinds of schools, the model has to be made in a way that it approximates a multi-site randomized trial. In this case, it is relevant that matching is made among individuals within the same cluster and that the balance of covariates across treatment and control groups is made within the same cluster (Hong & Raudenbush, 2006). However, when clusters are only an incidental part of the research design, for example, when individuals are drawn into treatment or control groups from different sites (neighbors, buildings or even schools), the design resembles a multi-site randomized experiment. In this case, matching can happen within or across clusters, and covariate balance can be achieved in the whole sample rather than within each cluster (Thoemmes & West, 2010).

This dissertation falls in the second category. Location of the private and public schools where students attend can be considered an "incidental" part of the design, since it is not expected, *a priori*, that private school effect is different *by design* in each state. The decision of whether the clustering is incidental or not, does not have to do with the actual size of the cluster effect. A given level of aggregation can have a large effect and still be considered "incidental" from the perspective of an ideal random design.

In this case, the hierarchical model for the estimation of the propensity score can adopt the form of a fixed effect model. In this case, the selection model would include dummy variables representing each cluster. The inclusion of such system of dummy variables (32 variables, one representing each Mexican state) would capture the variation in cluster means, despite the fact that the source of such variation may remain unknown. Therefore, in a fixed effect model there would be no need to include any cluster-level variables since they would be constant within each cluster. Following Thoemes and West (2010) the model may adopt the following form:

(1) $$\log it\left(e\left(x,w\right)\right)=\sum_{p=1}^{P}\beta_p X_i+\sum_{c=1}^{C}\beta_c C_i+\sum_{i=1}^{I}\beta_i C_i X_i$$

where $\log it\left(e\left(x,w\right)\right)$ is the estimated logit of the propensity score to enter into a private school, $\sum_{p=1}^{P}\beta_p X_i$ is a vector of student-level covariates and regression coefficients, the same variables included in calculation of the propensity score in the previous section, and *C* is a dummy variable indicating state membership, and $\sum_{i=1}^{I}\beta_i C_i X_i$ is a vector including all possible interactions between cluster and student-level covariates. Model (1) would render unbiased estimates of intercepts and slopes within each cluster and the propensity scores would be therefore unaffected by state-level differences.

However, there are two characteristics of the fixed effect model that might be of concern in the context of this research: first, the fitting of the fixed effect model requires a fairly large sample size within each state; and second, because each state has a different regression equation (the general equation plus the variable and coefficient of each state) the matching of private and public school students had to be made within each cluster (Thoemmes & West, 2010), which again requires large sample size within each state.

Unfortunately, as it can be seen in Table 11, the size of the private school student sample within some states is considerable small, even to the extent that in some states there are more regression coefficients that students enrolled in private schools. Therefore, this model and matching scheme, although it theoretically takes into account the nested structure of the data and it removes the sources of bias that arises from differences at the state level, it is not appropriate for the structure and characteristics of my data. However, for illustrative purposes, I fitted model (1) and present the results by state in Table 12.

There is an average of 85 public school students per state on common support, but only an average of 11 private school students in the sample in common support. Therefore, the consequences of fitting a model in such a small sample become very apparent in the table. For example, the range of the private school effect is so wide that it makes the results not trustworthy. The private school effect ranges from -136.00 test points in Campeche to 100 test points in Hidalgo. In both cases the private school student sample is very small. Also, as it would be expected, the standard error values are very large, which makes the results hugely imprecise.

Table 12: Estimated effect of private school in mathematics calculated by logistic regression with fixed effect by Mexican state, and matched though nearest neighbor matching.

State	No. of Students On Support		Test Results for Math				
	Urban Public	Private	Urban Public	Private	Difference	S.E.	T-stat
Aguascalientes	109	7	598.9	526.2	72.7	54.52	1.33
Baja California	55	8	511.3	503.0	8.3	41.15	0.20
Baja California Sur	97	5	538.8	515.4	23.4	62.48	0.37
Campeche	98	8	463.9	600.3	-136.3	47.09	-2.89
Coahuila	89	9	589.2	548.9	40.4	58.79	0.69
Colima	121	8	519.7	474.5	45.2	30.58	1.48
Chihuahua	60	7	588.9	510.2	78.7	66.37	1.19
Distrito Federal	50	9	564.0	471.1	92.9	29.75	3.12
Durango	47	6	604.2	526.6	77.6	89.26	0.87
Guanajuato	87	4	556.1	522.4	33.7	87.86	0.38
Hidalgo	65	11	578.7	478.2	100.5	39.35	2.55
Jalisco	75	11	520.1	602.3	-82.2	61.00	-1.35
México	73	16	566.6	545.5	21.2	45.49	0.47
Michoacán	64	12	519.7	536.4	-16.7	48.43	-0.34
Morelos	109	18	585.1	637.0	-52.0	74.89	-0.69
Nayarit	75	13	608.5	496.1	112.4	45.34	2.48
Nuevo León	39	13	561.6	480.8	80.9	50.37	1.61
Puebla	88	3	514.8	605.8	-91.0	86.57	-1.05
Querétaro	69	15	617.8	595.2	22.6	58.57	0.39
Quintana Roo	99	14	582.6	578.7	3.8	59.19	0.06
San Luis Potosí	74	13	562.2	516.5	45.7	39.19	1.17
Sinaloa	70	15	625.3	611.0	14.3	65.21	0.22
Sonora	96	27	601.8	542.7	59.2	35.28	1.68
Tabasco	114	13	604.4	514.2	90.2	44.19	2.04
Tamaulipas	93	12	585.1	588.7	-3.6	56.49	-0.06
Tlaxcala	143	11	544.7	530.2	14.5	42.77	0.34
Yucatán	145	5	653.8	541.6	112.2	60.57	1.85
Zacatecas	65	8	539.5	552.8	-13.3	51.02	-0.26

In the case of research where clustering is an incidental part of the design and the sample size within clusters is small, as in this dissertation, a better alternative is to model the hierarchical structure of the data in a way that it is possible to perform the matching across the whole sample, which overcome the within-cluster sample size limitation.

Thoemes and West (2010) suggest fitting a multi-level model without the random components, so the equation that estimates the propensity score is the same across the entire sample, allowing in this way the matching across clusters. In this context, I will not be able control for state-level unobserved covariates –as in the fixed effect model. However, I will include in the model a state-level variable indicating the percentage of the population within the state living behind the official level of poverty[10]. Table 13 presents the level of poverty (percentage of the state population living under the poverty line) of all Mexican states. I believe that this variable reflects the general level of educational opportunity within the state and that might also be proxy of other non-measured cultural and educational variations of families across states, as it has been shown in other research (Treviño & Treviño, 2004). The inclusion of this variable allows me to model the hierarchical structure of the data and still manage to keep the model parsimonious. The model would adopt the following form:

(2) $$\log it\left(e\left(x,w\right)\right) = \gamma_{00} + \sum_{p=1}^{P}\gamma_{p0}X_{ij} + \sum_{q=1}^{Q}\gamma_{0q}P_j + \sum_{i=1}^{I}\gamma_{1i}P_jX_{ij}$$

where $\log it\left(e\left(x,w\right)\right)$ is the estimated logit of the propensity score to enter into a private school, γ_{00} is the grand mean of math achievement for students in the sample, $\sum_{p=1}^{P}\gamma_{p0}X_{ij}$ is a vector of student-level covariates and regression coefficients, P is a variable indicating

[10] The official measure of poverty is determined by the National Council for the Evaluation of Social Policy (CONEVAL for its acronym in Spanish) and it is reported once a year. For more information see http://www.coneval.gob.mx

state-poverty level, and $\sum_{i=1}^{I}\gamma_{1i}P_jX_{ij}$ is a vector including all possible interactions between state poverty level and student-level covariates. The interaction effects are an important part of the model. The level-1 covariates (variables related to individual characteristics or characteristics of the student's family included in the original logistic model) might affect selection into private school different at every cluster level (in this case at the state level) as a function of the state level of poverty.

Table 13: Percentage of Mexican states living under the line of poverty

State	Poverty (%)
Aguascalientes	38.1
Baja California	31.5
Baja California Sur	31.0
Campeche	50.5
Coahuila	27.8
Colima	34.7
Chiapas	78.5
Chihuahua	38.8
Distrito Federal	28.5
Durango	51.6
Guanajuato	48.5
Guerrero	67.6
Hidalgo	54.7
Jalisco	37.0
México	42.9
Michoacán	54.7
Morelos	43.2
Nayarit	41.4
Nuevo León	21.0
Oaxaca	67.0
Puebla	61.5
Querétaro	41.4
Quintana Roo	34.6
San Luis Potosí	52.4
Sinaloa	36.7
Sonora	33.1
Tabasco	57.1
Tamaulipas	39.0
Tlaxcala	60.3
Veracruz	57.6
Yucatán	48.3
Zacatecas	60.2

Source: CONEVAL, 2010

The model was fitted using the xtemelogit function of stata. Results for the fitting of this model are reported in Table A2 in the Appendix. According to the information presented in the table, I cannot reject the null hypothesis that states that all logistic regression coefficients are equal to zero at the 1% significant level (Wald chi2 = 402.02, Prob > chi2 = 0.0000). Therefore, the results indicate that the fitting of multilevel model (2), which takes into account the state level of poverty –in addition to the student-level covariates-, is appropriate to estimate the propensity scores for the matching analysis.

4.4.3 Selection of Final Propensity Score Model and Matching Algorithm

After fitting model (2) I performed nearest neighbor propensity score matching. Table 14 presents the results and the computation of the private school advantage. As in Table 6, the first raw shows the straight up difference for all students, and the second raw (labeled ATT) shows the difference for the matched groups.

Table 14: Differences in ATT in Mathematics between students with *Oportunidades* scholarship in Public and Private schools, using the nearest neighbor matching estimator after estimating propensity score through a multilevel model (On support: 2,653 public students, 301 private students)

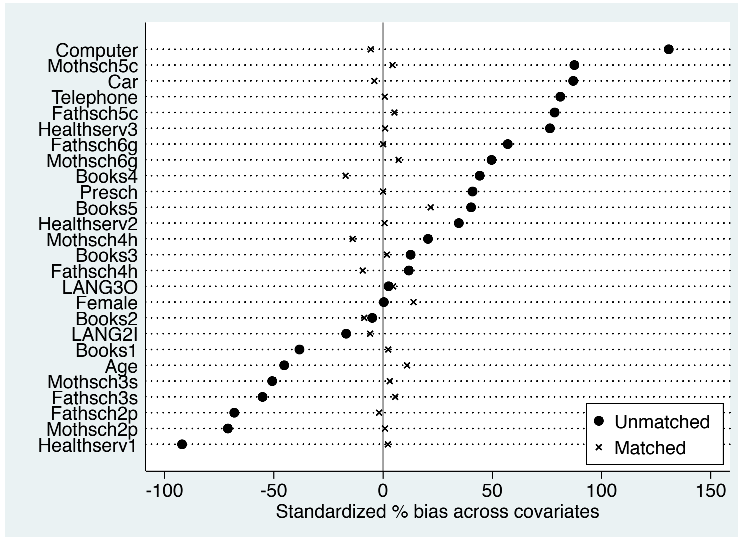
Sample	Private School	Public School	Difference	S.E.	T-stat
Unmatched	573.71	494.34	79.37	5.47	14.50
ATT	573.71	525.87	47.84	13.29	3.60

According to Table 14, private school students who are beneficiaries of *Oportunidades* program outperformed their public counterparts by on average of 48 test points or 48% of a standard deviation.

The multilevel model is a better choice of obtaining the propensity scores for the students in the sample. In addition to including in the model the same set of first-level variables included in (1), it also account for inter-state variations in the probability of enrolling in private school as a consequence of the inclusion of a second level variable (Poverty) and the interaction terms between this variable and all personal single-level variables.

In addition to that, the propensity scores obtained through fitting the multi-level model (2) also allow for better quality of matching than the matching obtained through the fitting of a single-level logistic regression model and the use of nearest neighbor matching performed after, as shown in the previous section. The mean of standardized percentage bias for all variables included in the logistic regression model is 6.48, whereas it is 5.88 for the multilevel model. Graph 1 shows the standardized % bias by variable. It is clear that this model is doing a good job of balancing variables between the two groups. Therefore, further analyses are conducted using information from the multilevel model.

Graph 1: Plot of standardized % bias by variable, after matching using the nearest neighbor matching algorithm after estimating propensity score Multilevel Model.



4.4.4 Unobserved Heterogeneity and Rosenbaum Bounds

Rosenbaum (2002, 2005) suggests to be mindful of a distinction between overt bias and hidden bias. Overt bias is visible to the researcher and is usually reflected in the variables contained in the data. Hidden bias, on the other hand, is not visible to the researcher; the information that represents it is not recorded. Unlike overt bias, which can be properly modeled and corrected through matching –as I did in the previous sections of this research- unobserved heterogeneity might affect both the probability of selection into treatment -- private school in this case -- and the ultimate outcome -- achievement in math (Guo & Fraser, 2010).

In the absent of randomization, which automatically avoids hidden bias in observational studies, it is important to assess the extent to which hidden bias might affect the estimates of treatment to the point in which they render them untrustworthy (Guo & Fraser, 2010; Rosenbaum, 2002).

To assess how robust are the matching estimates with respect to unobservable variables, I conducted the Rosenbaum bound sensitivity analysis to assess how strong the hidden selection bias would need to be to alter the matching estimates. The basic idea is to identify a number Γ (gamma), which would capture the degree of association of a hidden characteristic (student motivation, for example) with the treatment and outcome, necessary for it to explain the observed impact (Duvendack & Palmer-Jones, 2012). This unit Γ is expressed as log odds, and the purpose is identify a cutoff point of Γ at which the matching estimates would be statistically insignificant. In the context of the present research, the basic idea is to find out if the inference about the effect of private schooling in the achievement in math of poor students may be altered by unobserved factors to the point that it undermine the results drawn from the matching analysis (Caliendo & Kopeinig, 2005).

This approach has been successfully applied in several research studies across many fields (Aakvik, 2001; Caliendo, Reinhard, & Thomsen, 2005; Duvendack & Palmer-Jones, 2012; Han, 2012; Mavromaras, McGuinness, & King Fok, 2007). I calculated the Rosenbaum bounds for the estimated average treatment effect of private school in math. I obtained the results by performing the “rbounds” command in Stata (Diprete & Gangl, 2004).

Table 15 presents the results. A p-value above 0.05 indicates a critical level of gamma that renders the matching estimates invalid (Guo & Fraser, 2010).

Table 15: Rosenbaum Bound Sensitivity Test for the Private School Effect in Math Achievement Test.

Gamma	Rosenbaum Bounds	
Γ	Minimum	Maximum
1	0	3.00E-10
1.1	2.30E-12	2.10E-08
1	1.60E-14	6.30E-07
1.3	1.10E-16	9.90E-06
1.4	0	0.000093
1.5	0	0.000576
1.6	0	0.002575
1.7	0	0.00878
1.8	0	0.023951
1.9	**0**	**0.054289**
2	0	0.10542
2.1	0	0.179856

Γ = log odds of differential assignment due to unobserved factors

Results show that my estimation of the effect of private school on math (48% of a standard deviation) is fairly robust to bias from hidden variables. A hidden variable (or a set of them) would need to increase the odds of enrolling into private school by 90% ($\Gamma=1.9$, $p<0.054$) to make the private school effect invalid.

According to DiPrete and Ganglg (2004), the Rossenbaum bounds represent the "worst-case" scenario with respect to the robustness of matching estimates, meaning that it is very likely that the actual bias associated to hidden variables is actually smaller than the value of Γ .

The study appears to be robust against hidden bias.

4.5 Interpreting the Effect Size Estimates in the Context of Other Studies

The 0.48 sd effect size of private school identified in the previous section, is larger relative to much of the existing literature, especially if we compare it to the results of true experiments (or good quasi-experiments) of private schools conducted in the U.S. One example is the results of The New York City school choice program, the largest private school scholarship experiment conducted to date, which provided vouchers for 1,300 children from low-economic background in grades K-4 in the New York City public schools (Mayer, Peterson, Myers, Clark Tuttle, & Howell, 202). Scholarship recipients were selected randomly through a lottery held in 1997. The impact of a voucher offer on test scores over a three-year period (the intent to treat effect) was statistically significant for African Americans. The effect size was 0.14 standard deviation for reading and 0.26 standard deviations for math[11]. The estimated effect of vouchers on math in this case is almost half the size the one found in this dissertation. However, if we consider the impact of actually attending a private school (the treatment effect), whether for one, two or three years, which is a more comparable result to the findings obtained in this research (*Oportunidades* children, who actually attended private schools), the estimate is 0.37 standard deviations for the combined test scores (reading and mathematics) for African Americans (Mayer et al., 202). This result is still 30% smaller that the 0.48 size effect reported in the dissertation, but not as far away than the intent to treatment estimate.

The private school effects found in this dissertation are also larger if we compare it to results of private schools across different states. In an evaluation conducted by the Institute of Education Sciences, researchers evaluated the impact of 36 charter middle schools in 15 states, all of which selected students based on randomized admission

[11] In a reexamination of the data of the New York City school choice program, Kruger and Zhu (202) found that after considering the full sample (including those with missing baseline data, excluded from the original study) the effect of the voucher program in African Americans decreases importantly and became not statistically significant. They also found the results for this ethnic group to be sensitive to the way race/ethnicity was defined. The authors of the original study have also replied to this argument (Myers & Mayer, 2003). There does not seem to be a consensus yet as to the validity of the results.

lotteries (Gleason, Clark, Clark Tuttle, Dwoyer, & Silverberg, 2010). Although there is a large variation in the effect of the charter schools included in the study, on average, charter schools with the largest proportion of disadvantaged students had a positive accumulated effect on the second year after the lottery on math scores of 0.18 standard deviations. This is less than half the effect found in my dissertation.

In a report containing both, observational and lottery studies, about Boston schools, researchers found that for each year of attendance to a Charter middle school, there is an estimated raise in student achievement of 0.18 to 0.54 standard deviations in mathematics relative to those attending Boston public schools (Abdulkadiroglu et al., 2009)[12]. This shows that only in the more optimistic of scenarios, the private school effect would be closer to the estimates presented in this dissertation.

I hypothesize that there are two factors that may be responsible for the larger size of the private school estimate reported in this dissertation relative to effect size found in previous research. One possible explanation is that the actual counterfactual of the study is private school effect with only poor families in urban areas in Mexico. In this way, the large results may be only associated to private schooling for the poor in urban settings and not generalizable to all private schools serving the poor in Mexico. A second potential explanation may have to do with the nature of the treatment. I have restricted my analyses to families who received a scholarship as part of a conditional cash transfer program (CCT) targeting population living in extreme poverty. Therefore, the larger effects may be explained by the interaction of these other program components with

[12] The bottom limit results are estimated through the implementation of an observational study, using baseline scores and other demographic variables in the model; the upper limit of this effect is was actually calculated with a model based on lottery results and the inclusion of demographic variables in the model.

private schooling, or by the context that *Oportunidades* creates, which would hypothetically enable students to more readily benefit from the superior quality of private schools.

In the following section I will discuss these possible explanations in detail.

4.5.1 Targeting the Right Counterfactual

The focus of this study is poor students attending private schools in urban cities in Mexico. Targeting the right counterfactual may be responsible in part for the large private school effects identified in this dissertation.

Studies covering a wide variety of states and districts in the US show non-positive average effects of charter schools (Zimmer et al., 2003) or small negative effects for the white majority (Center for Research on Education Outcomes, 2013). Private school effects, in general, tend to be larger for the poor and the minority living in urban areas, like the case of the population studied in this dissertation.

According to existing literature, the urban poor population (which very often is part to a minority group) is the one benefiting the most from private schooling. In the case of the New York City voucher experiment, most students attending private schools perform at similar levels than those attending public schools (Mayer et al., 202). In other words, private school did not seem to make a difference for the predominant population. However, there was a significant voucher impact on test scores (0.14 and 0.26 standard deviations) for African Americans, a population disproportionally poor. In a report analyzing the effect of 36 charter middle schools across 15 states, one of the main findings is that charter school's impacts on student achievement are inversely related to students' family income level (Gleason et al., 2010). In this study, charter schools serving more low-income students had a statistically significant positive effect on math test scores. On average, charter schools with the largest proportion of disadvantaged students had a positive effect on math scores of 0.18 s.d. On the other hand, there was an average negative effect of 0.24 s.d. for schools serving fewer economically disadvantaged students. In addition to that, Charter middle schools in large urban areas had significant impact on achievement, as opposed to suburban charter schools. Schools located in urban areas had an impact on year 2 math scores of 0.16 standard deviations, compared to the negative effects found on suburban area (Gleason et al., 2010). Abdulkadiroglu and his colleagues (2009) found similar results in a study comparing regular, charter and pilot schools in the Boston area. In this case, urban charter schools, which have an average of 73 percent of students qualifying for free or reduced price lunch, have a positive effect on learning.

In a recent study that analyzes charter schools in 27 different states (including data from more than 1.5 million students in charter schools and matched comparison groups), researchers found that Black students, student living in poverty, and English language learners were the ones truly benefitting from charter schooling (Center for Research on Education Outcomes, 2013). In fact, charter schools are even more beneficial to students that combine multiple challenges, like being Spanish or Black living under poverty or with language limitations. According to this study, poor black students who attend charter schools gain 36 additional days of learning in math and 29 days of learning in reading. Hispanic ELL students benefited even more. By attending charter schools they gained 50 additional days of learning in reading and 43 days of additional learning in math, in contrast with comparable students in public schools (Center for Research on Education Outcomes, 2013).

Of a special interest is a multi-year causal study that analyzes the achievement of 93 percent of the New York City charter school students enrolled in grade 3 through 12 (Hoxby, Muraka, & Kang, September 2009). Since Charter school applicants in New York City tend to be more likely black and poor than the average student in New York's traditional public schools, the results of this study are particularly interesting for this dissertation, focusing in the effect of private schooling on the urban poor in Mexico. A student who attended charter school for all grades kindergarten through eight would close about 86% of the racial achievement gap in mathematics and 66% of the achievement gap in English in the state.

The literature on voucher schools adhered to the No Excuses approach to education also confirms the urban-poor-minority exclusive effect of private schooling. The "No Excuses" schools emphasize a series of educational practices though to be directly link to student achievement, such as frequent testing, increased instructional time, parental involvement, strict student discipline, and focus on math and reading achievement (Carter, 2000; Thernstrom & Therenstrom, 2004). Angrist et al. (2011) found that Massachusetts No Excuses urban charter schools increase student achievement in math as opposed to Massachusetts non-urban charter schools. In fact, charter schools are more effective with minority low-baseline achievers, who are predominantly poor students.

In a quasi-experimental evaluation, researchers found that schools affiliated with the Knowledge is Power Program (KIPP), which are emblematic of the No Excuses approach to education, show achievement gains for limited English proficiency (LEP) students, special education students, and low-baseline students, but not for any other student group (Angrist, Dynarski, Kane, Pathak, & Walters, 2010). This study was conducted in the Academy Lynn KIPP charter school, a New England school characterized by a predominant Hispanic population (Angrist et al., 2010).

The research on the performance of private Catholic schools also confirms that the private school's effect is mainly positive in the case of poor urban students. For example, Evans (1995) finds that Catholic private schools have a positive effect on the student's probability of high school completion and the probability of starting college. The effect in this case is larger if the student is black and living in urban areas and practically no existent for any other group. Neal (1997) found that Catholic schools, concentrated in urban areas, do increase significantly the educational attainment of urban students, especially of urban minorities. On the other hand, the private school effect is modest for urban whites and almost non-existent for suburban students Results were similar for more recent cohorts. Grogger et al. (2000) found that Catholic high school attendance increases the probability of graduation by about 24 percent for urban minorities, and that the results for the predominant group are not significant. Altonji et al. (2005) report that Catholic high schools increased graduation rates and college attendance rates for urban minorities.

This review shows that private school advantage holds mainly for the urban poor, which is the case of the group studied in this research: poor families looking for better schooling options in urban areas in Mexico. My contention is that the use of the right counterfactual may help explaining the larger effects found in this research.

4.5.2 Nature of the Treatment

Oportunidades is a poverty alleviation program targeting families living in extreme poverty in Mexico. This program articulates different development initiatives of the federal government aimed at combating poverty nationwide. In addition to the cash transfer component, *Oportunidades* comprises a variety of social programs in the areas of financial inclusion, self-employment, education, health, diet habits, and general wellbeing. This kind of model emphasizing the provision of wrap-around services takes into account the whole need of the poor family, including the needs of the children. It is very likely that the large effects of private schooling found in this dissertation are the product of the interaction of a comprehensive set of interventions with private schooling. In this scenario, the bundle of services and programs comprised in *Oportunidades* would produce effects in achievement only in combination with private school characteristics, either measured or unmeasured in this study. For example, it might be the case that the increase on student school attendance caused by *Oportunidades* (as it will be shown later in this section), only makes a difference in achievement in students attending private schools, if students in private schools, for example, experience more learning time than students in public schools. Another possible explanation is that the presumably superior higher quality of private schools are more likely to have effect on children for whom other supports are present –as provided by *Oportunidades*—than for children facing the stresses of poverty. So *Oportunidades* creates a context that enables students to more readily benefit from the superior quality of a private education, and for this reason the effects found in this research are higher than the effects documented in other studies where those enabling conditions of a comprehensive poverty alleviation program are not present.

One of the components of *Oportunidades* that might be positively interacting with private schooling, is the income support element provided by the program in the way of a cash transfer. Researchers have provided different explanations as for why family income might affect children development. Given the link between poverty in an early age and children development, supporting the income of families with young children may have long-lasting effects on educational outcomes. For example, Dahl and Lochner (2008) use variations in the amount of the Earned Income Tax Credit (EITC) as an instrumental variable to measure the causal impact of increase of income in educational achievement. They found that a $1,000 increase in income raises combined math and reading test scores by 6 percent standard deviations. Also, income support policies ensure a basic level of sustenance to families, which might not only help them escape poverty, but also provide them with a certain sense of relieve and tranquility. In fact, one of the vehicles through which poverty might negatively influence children's outcomes, is through the effects that parental psychological distress commonly associated to poverty causes (McLoyd, 1990). Parents in poverty are much likely to experience high level of psychological distress, which in turn affects children's socioemotional wellbeing through its impact on parent's behavior and practices towards the children. For example, Parker et al. (1999) report that poverty adversely affects children's outcomes, especially school readiness. Attitudes and practices commonly associated to poverty and the stress it produces, such as parental aggravation and strictness, have a negative effect on child's distractibility and hostility in the classroom, which in turn predict a decrease in associative vocabulary skills. The income relief located at the center of *Oportunidades* might be positively affecting educational achievement through this mean[13]. Of course, this would only be true if the positive family effect produced by this component of the program positively interacts with characteristics only present or predominant in private schools.

Besides alleviating family and environmental stress, there are other pathways through which *Oportunidades* may affect child development and educational outcomes. *Oportunidades* may also positively affect parental investment. For example, Gordon et al (2008) reported that increases in incomes generated by expansion of the EITC program targeting the poor, improved low-income children's educational achievement. In the same sense, research in Mexico has shown that there is a positive association between income level and the size of family educational investment on their children, such as investment in books and other resources associated with better educational outcomes (Treviño, 2005).

In addition to that, parents who are poor have more mental health problems than economically advantaged parents, which translate into child rearing problems (McLoyd, 1990). It is possible that the poverty alleviation provided by the program is contributing positively to the mental health of parents and, through this way, the wellbeing of children. But *Oportunidades* might also positively affect the IQ of children. Research has proved that persistent poverty has detrimental effects on IQ and school achievement (McLoyd, 1998). The economic relieve provided to the families by *Oportunidades* might have positive effects on cognitive development of children and their performance in school.

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[13] See Magnuson and Votruba-Drzal (2008) for a complete review of consequences of childhood poverty.

But the effect of *Oportunidades* in children achievement can be even more direct than what the arguments presented above implied. A number of recent studies suggest that wrap-around interventions with an educational program at the center might be responsible for large achievement effects on children. For example, using admission lotteries Curto and Fryer (2011) reported that a charter boarding school in Washington DC called SEED, raised substantially the educational achievement of participants. SEED combines a charter school adhered to the "No Excuses" model and a five-day-a-week boarding program. Attending a SEED school increased student achievement in mathematics by 0.23 standard deviations per year. It is very difficult to technically disentangle the effect of the individual component of these comprehensive programs. In this case, for example, we cannot say with certainty if the achievement effect is mainly due to the charter school or if it is a combined effect of the charter and the boarding component.

Another example of this kind of comprehensive intervention is the Harlem Children's Zone (HCZ). The HCZ combines community programs with charter schooling. According to a lottery and instrumental variable identification strategy, Dobbie and Fryer (2009) found that the effects of the program in elementary school, closed the racial achievement gap in English Language Art (ELA) and in mathematics. Students in the HCZ elementary school raised their achievement 0.80 to 1.5 standard deviations in math and ELA. These results are even larger than the ones found in this dissertation. Authors of this study believe that it is the interaction of community programs and school intervention what produces these large results. They even entertained the idea that the community programs work as a key "technology shifter" in the manufacture of achievement.

The interaction between private schooling and the bundle of complementary social programs comprised in *Oportunidades*, might explain in part the large private school effect on achievement found in this dissertation. *Oportunidades* might have an effect on student achievement by providing certain home conditions and incentives that positively interact with private schooling. In fact, different studies have already found that *Oportunidades* has a positive significant effect on school enrollment (Parker, Todd, & Wolpin, 2006), school attainment (Behrman, Gallardo-García, Parker, Todd, & Vélez-Grajales, 2010; Lalive & Cattaneo, 2006) and students' time devoted to homework (Behrman et al., 2010). Researchers have found that there are even significant spillover effects of *Oportunidades* to program non-participants (Lalive & Cattaneo, 2006).

All this evidence shows that the large size of the private school advantage could be attributed in part to the fact that the treatment under study is much more complex than just private schooling.

4.6 Summary and Discussion of Results of Private School Advantage

With the analyses presented in the previous sections, I am ready to answer my first research question and state that there is indeed a private school advantage. On average, private school students who are beneficiaries of *Oportunidades* program outperformed their public counterparts by an average of 48 test points, or 48% of a standard deviation.

Although all students included in this research are considered poor (they all are beneficiaries of *Oportunidades*) differences in important family variables suggest that students attending private schools are relatively more advantaged than those attending public schools. Therefore, it is important to account statistically for these differences associated with the selection bias. The results obtained through propensity score matching are technically reliable. The findings have passed different robustness checks. Results are robust to the use of different matching estimators, and also robust to the observed and hidden bias that may arise from the geographic location of schools. Also, the performance of Rosenbaum bound sensitivity analysis has shown that a hidden bias would need to increase the odds of entering into a private school by 90% to actually affect the estimation of the private school advantage.

The private school effects found through propensity score analysis are indeed very large compared to previous literature. As explained earlier, these large results might have to do in part with two factors. On the one hand, the use of the right counterfactual for this research: poor students attending private urban schools. In this way, the private school advantage would be larger than if non-urban poor were part of the sample. On the other hand, large results might be attributed to the fact that all students in the sample attending private schools are all beneficiaries of *Oportunidades*, a comprehensive poverty alleviation program. This implies that the treatment is more complex than just private schooling, and that some components of *Oportundiades* might be positively interacting with private schooling to produce these large effects.

For poor students, schooling in general seems to make more of a difference than for non-poor students. I estimated the intraclass correlation of poor students' achievement in mathematics across schools. The results show that 30% of the variation in student achievement is due to difference among schools (ρ=0.30). This result is larger if we compare it to the intraclass correlation of regular students in mathematics, which is about 20% according to previous research (Treviño & Treviño, 2004).

There are some indications that the weight that SES has in student achievement has been decreasing in the last years in Mexico. The 2012 Pisa Report (OECD, 2014) shows that the role that SES has on explaining the achievement gap between disadvantaged students and those that are economically better off has decreased in the last years. However, the difference in school resources among the Mexican schools is one of the largest in the OECD countries, and the within-country variation in test scores compared with other countries is still very large. The information on the PISA report, therefore, seems to be in contrast with the findings reported in this dissertation. A possible explanation might be related to the fact that the Mexican educational system tends to become less unequal in the higher educational levels. PISA report is based on 15-year old students, mainly in low-middle school, whereas I am reporting results for elementary school, an educational level that presents different sociodemographic profile. In addition to that, I am concentrating my analyses on the performance of poor students in private schools with respect to poor students in public schools. This population is a more restricted sample that the one used for the PISA evaluation, which was representative of the whole student population. The population focus of this research tends to have a higher variance than the general student population and, therefore, tends to be more sensitive a changes in school resources.

5. The Determinants of Private School Advantage: What Factors Make a Difference?

In this section I am presenting the statistical analyses aimed at answering my second research question. Now that I have established that there is indeed a private school advantage, it is important to identify what school factors explain this advantage, beyond the differences between types of students that I attempted to correct through propensity score matching.

I fitted several taxonomies of regression models, regressing student's achievement in Mathematics on PRIVATE. I controlled for self-sorting into educational sector by including in the model the propensity score variable (pscore) created in the last section as a product of the propensity score matching estimation. I also included a set of peer group variables in the baseline model. Peer group effect is one of the most important factors explaining educational achievement. Although it is true that there has not been any previous educational policy in Mexico that attempted to alter this important educational input, it is not possible to properly identify the effect other school factors without accounting for this effect. I then added systematically to the base-line model different set of predictors measuring the four main factors of school performance focus of this dissertation: physical resources, school management, teacher quality, and teaching practices and classroom organization.

5.1 Analytical Methodology

In this dissertation, achievement is modeled following this specification[14]:

(3) $A = f(I, B, SI, P)$

where achievement *A* is a function of a vector of student's ascribed characteristics *I*, such as and innate abilities (intelligence, for example); *B* is a vector of family background and socioeconomic status; *SI* is a vector of school inputs and management; and *P* is a vector of influences of peer group characteristics.

I am interested in analyzing the extent to what school inputs (*SI*) explain the private school advantage found in the previous section. Especially, I am interested in analyzing the school factors object of most of the educational policies implemented in Mexico. To do this, first I need to account for the effect of innate ability, family background, and peer-group characteristics, and then isolate the effect that the inputs of interest have in student achievement in mathematics among poor students in Mexico: physical resources, school management, teacher quality, and teaching practices and school organization. My hypothesis is that if I consider school differences in these inputs (once I account for the effects of family background and peer-group characteristics), there is no really significant difference between both public and private schools, and that the private school advantage found in the previous section should fade away.

[14] This explanation falls in the tradition of education production function. For an early discussion on the estimation of educational production functions, see Hanushek (1979)

To fully explain student achievement, therefore, it is necessary to use information about innate ability, family background and peer-group characteristics. However, it is very difficult to include student's ascribed characteristics (I) in education production functions, unless information about cognitive skills is available. In my dissertation, however, I do not count with cognitive test results or information about previous achievement, so achievement results can be affected by personal skills without having a way to identify it. Therefore, the only way to really estimate the effects of the main school inputs object of policy makers in Mexico in the context of the data at hand is to remove the effect of family background. It would also be necessary to account for peer-group effects, one of the factors with a recurrent effect in the literature.

Family socioeconomic background has been part of educational production function since the earlier studies appeared after the Coleman Report (Hanushek, 1986) and it has been almost unequivocally associated to achievement differences and variations in other well-being outcomes (Bradley & Corwyn, 2002). If family and environment has important weight in student achievement, it is likely that students from more educated families self-select themselves into private school, which would bias the estimates of mathematics achievement upwards. On the other hand, peer group composition is at the same time one of the dimensions included in education production functions since the late 60's and one of the most difficult to identify in statistical models (Hanushek, 1979; Murnane, 1975, 1984). Attending a school in which most students come from homes that they themselves provide strong support for academic achievement may also have a positive effect on the achievement of the individual student.

5.1.2 Identification Strategy

I am fitting a taxonomy of regression models, regressing student's achievement in Mathematics (MATH) on my question predictor, PRIVATE, and main baseline variables. The objective is to form a baseline control model that removes the effect of family background and peer-group composition in the school. The base-line model has the following form:

(4)

$$MATH_{ij} = \beta_0 + \beta_1 \Pr ivate_j + \beta_2 \Pr opensity + \sum_{i=1} \beta_3 PE_{ij} + \varepsilon_{ij}$$

Where Private is a variable indicating whether the student belongs to a private school or not, *Propensity* is a variable containing the propensity scores for each student I obtained from fitting model (2) from the previous section, and $\sum_{i=1} \beta_3 PE$ is a vector of peer-group variables and coefficients, and ε_{ij} is an individual random error. By introducing in the model the propensity score, I am directly controlling for the effect of background variables in student achievement, at least as it pertains to overt bias. In addition to that, by introducing a set of variables measuring peer group effect, I am controlling for the aggregation effect of peer-group composition. It is important to mention that some of the variables used to account for the student's peer-group have some important limitations and, therefore, it is important to exercise caution when interpreting these results. In this way, the magnitude and direction of β_1, the coefficient of Private, would capture only the private school advantage, net of background and peer-group effects.

After fitting the baseline control model, I systematically included covariates that describe school physical resources, school management, teacher quality and teaching practices and classroom organization to the baseline control model. The final model has the following form:

$$MATH_{ij} = \beta_0 + \beta_1 \Pr ivate_j + \beta_2 \Pr opensity + \sum_{i=1} \beta_3 PE_{ij} + \sum_{i=1} \beta_3 Phys\operatorname{Re} s + \sum_{i=1} \beta_3 SchMng + \sum_{i=1} \beta_3 TQ + \sum_{i=1} \beta_3 TpractCO_{ij} + \varepsilon_{ij} \tag{5}$$

Where *PhysRes* is a vector of school physical resources, *SchMng* represents a vector of school management variables, *TQ* is a vector of teacher quality variables, and *TpractCO* is a vector of teacher practices and classroom organization variables. The rest of the variables are defined as in model (4). I am examining how the estimated coefficient on predictor PRIVATE changes as variables accounting for level of physical resources, school management, teacher quality, teaching practices and classroom organization, are added to the model. If the achievement differential were explained in part by these predominant school factors, I would expect my estimate of β_1, to decrease progressively on the introduction of these predictors. A positive and statistically significant β_1 coefficient remaining after the final model has been estimated would indicate that a portion of the private school advantage is not fully captured by variables representing level of physical resources, school management, teacher quality, and teaching practices and classroom organization, net of background variables and peer-group effects.

I will first fit models with the baseline model and each particular school factor, and then I will fit a combined model with all factors added to the baseline model.

5.1.3 Contextual Effects

There is still some source of bias that can arise from the context where the public and private schools are located. One way to take into account these contextual factors is to build a mixed model by introducing a set of dummies representing each of the 32 states where the public and private schools are located. Unfortunately, as I showed in Section 4.4.2, the number of cases by state and the number of variables in the model makes this estimation not feasible. Including a full set of the covariates considered in this research in a small inter-state sample makes the variance very high, which leads to problems in the correct estimation of standard errors and makes the results not trustworthy.

Therefore, instead of building a fixed effects model with indicators of state, I will build a fixed effect model with indicators of the poverty region. I divided Mexico into four poverty regions. Each state belongs to one of these regions depending on the percentage of the population that live under the official line of poverty within each state. Categories go from 1 to 4, depending of the extension of poverty within the state. States that have between 21% and 34.7% of their population below the poverty level are categorized as 1. States that have between 34.8% and 42.9% of their population below the poverty level are categorized as 2. Those states with 43% and 54.7% of their population living in poverty are categorized as 3. And finally, the states with 54.8% and 78.5 of their population living and poverty are categorized as 4. Table 16 shows the distribution of Mexican states according to its poverty category.

To ensure the correct estimation of models since very beginning, I added the fixed effect component to models (4) and (5). The new baseline control model is as follows:

(6) $$MATH_{ij} = \beta_0 + \beta_1 \Pr ivate_j + \beta_2 \Pr opensity + \sum_{i=1} \beta_3 PE_{ij} + \sum_{c=1}^{R} \beta_c R_i + \varepsilon_{ij}$$

Where *R* is a dummy system indicating regional poverty level and the rest of the variables are defined as in model (4).

Table 16: Percentage of Mexican states living under the line of poverty

State	Poverty Category
Nuevo León	1
Coahuila	1
Distrito Federal	1
Baja California Sur	1
Baja California	1
Sonora	1
Quintana Roo	1
Colima	1
Sinaloa	2
Jalisco	2
Aguascalientes	2
Chihuahua	2
Tamaulipas	2
Nayarit	2
Querétaro	2
México	2
Morelos	3
Yucatán	3
Guanajuato	3
Campeche	3
Durango	3
San Luis Potosí	3
Hidalgo	3
Michoacán	3
Tabasco	4
Veracruz	4
Zacatecas	4
Tlaxcala	4
Puebla	4
Oaxaca	4
Guerrero	4
Chiapas	4

And the new identification model for school factors is:

$$MATH_{ij} = \beta_0 + \beta_1 \Pr ivate_j + \beta_2 \Pr opensity + \sum_{i=1} \beta_3 PE_{ij} + \sum_{i=1} \beta_3 Phys\operatorname{Re} s + \sum_{i=1} \beta_3 SchMng + \sum_{i=1} \beta_3 TQ + \sum_{i=1} \beta_3 TpractCO_{ij} + \sum_{c=1}^{R} \beta_c R_i + \varepsilon_{ij} \quad (7)$$

with the inclusion as well of *R* as a dummy system indicating regional poverty level and the rest of the variables defined as before.

Models (6) and (7) are the ones that are going to be estimated to answer my second research question. Fixed effects are going to be "absorbed", in the sense that they will be taken into account for the estimation of all variables in the model, but are not going to be reported, since they are not really an interest of this research.

5.2 Measures and Descriptive Statistics.

5.2.1 Measures

5.2.1.1 Baseline Control Model Variables

Propensity-Score Variable. This variable represents the conditional probability of getting into a private school after fitting model (6). Values can range from 0 to 1.

Peer-group composition. To describe peer group composition, I created nine variables, divided in two groups: Family Expectations and Socio-Economic Status.

Family Expectations and Educational Interests is measured by three variables: the percentage of students in the school whose educational expectation is to attain a bachelor's degree or a graduate education (STUDENTEXP_CLASSPER); the percentage of students in the school whose parents expect them to attain either a bachelor's or a graduate education (PARENTALEXP_CLASSPER); the average score in the index PARENTALINT index of the students in the school (PARENTALINT_CLASSPER). It is important to point out that some of the variable within this group are in fact indirect measures of peer-group. This is the case of the variable measuring student's parental expectations and parental interests (PARENTALEXP_CLASSPER and PARENTALINT_CLASSPER). These measures are quite different from the more common measures used in the literature, such as average achievement or racial composition of the school. Nonetheless, I decided to include them in the following analyses because I believe they reflect important differences about the student body that are part of public and private schools. However, interpretation about the weight of these variables in the statistical models should be taken with caution.

Socio-Economic Status is measured by four variables: the percentage of students in the school whose family receive medical attention either at the IMSS, ISSSTE or similar institutions, or go to private clinics and private health services (HEALTHSERV_CLASSPER); the percentage of students within the school that work besides studying (WORK_CLASSPER); the percentage of students within the school that have a computer at home (COMPUTER_CLASSPER); and the percentage of students within the school that have a car at home (CAR_CLASSPER).

Finally, Family Cultural Capital is measured by two variables: the percentage of students in the school that have 100 or more books at home (BOOKS_CLASSPER); and the percentage of students in the school whose mother's maximum level of schooling is college or beyond (MOTHSCH_CLASSPER).

5.2.1.2 Question Predictors

School- physical resources. To record school physical resources, I am using four variables. The infrastructure of the school is measured by an index of School Physical Resources (SCHOOLPHYSRES) constructed from information about the availability and conditions of basic infrastructural resources, such as student bathrooms, sports facilities, all-purpose room, backyard, library, and media center. The school pedagogical resources is measured by two indexes, School Pedagogical Resources (SCHOOLPEDRES) and School Computer Resources (SCHOOLCOMPRES), which combined measured the existence and number of certain basic teaching resources, such as stereo or recorder, dvd player, television, computer, computer projector, etc. All indexes have a mean of 0 and an sd of 1. The fourth variables is a set of dummy variables measuring the number of books available at the school (SCHOOLBOOKS1-SCHOOLBOOKS4), from 100 or less to more than 400 books. The omitted category is SCHOOLBOOKS1.

School Management. To measure school management, I created four variables: an index of Principal Support (PRINCIPALSUPP), which measures the extent to which the school principal provides support and guidance to the teacher; an index of Teacher Collaborative Work (TEACHCOLLWORK), which assess the quality of the relationship of the teacher with his or her colleagues at the school, especially the quality of the communication among them, the level of support he or she receives from them, and the team work. The two other variables are in fact two sets of dummy variables: one set of dummy variables measures indicate the number of classes cancelled during the academic year at the school for any reason (CLASSLOSS0-CLASSLOSS4), anything from the schedule of teaching meetings to the occurrence of teaching strikes. The omitted category is CLASSLOSS0. The second set of dummy variables measure the actual length of the school day in terms of hours, which can go from 4.5 hours or less (SCHOOLDAYHRS1) to 6.5 hours or more (SCHOOLDAYHRS3). The omitted category is SCHOOLDAYHRS1

Teacher quality. To record teacher quality, I am including two groups of dummy variables. Teacher education is measured by a vector of dummy variables, TCHEDU1B through TCHEDU5G, ranging from "high school or less" to "graduate school". My omitted category is TCHEDU1B. I am measuring Teacher Experience by a group of dummy variables indicating the number of years the teacher has worked in the profession, from two or less years of experience to 16 or more years (TEACHEXP1- TEACHEXP4). The omitted category is TEACHEXP1.

Teaching Practices and Classroom Organization. I am including six groups of variables to measuring teaching practices and classroom organization. I measure Curriculum Coverage using a set of four dummy variables (CURRICOVERAGE1 to CURRICUVOERAGE4), measuring the amount of curriculum the teacher expects to cover during the academic year (from 50% or less of the academic curriculum to 100%). The omitted category is CURRICOVERGE1. To measure the actual practices of teachers in the school, I created four indexes that convey the level to which teachers include good teaching techniques in their regular practice and in the teaching of Spanish and Mathematics. The Good Pedagogy Index (GOODPEDAGOGY) encompasses the frequency in which teachers practice sound general pedagogical practices, such as explaining students how to correct their mistakes, use pedagogical resources other than the blackboard, allow the students to express their opinions, or teach the students how to investigate. There are two Math Pedagogy indexes (MATHPED and MATHPEDRSCOLLWK), indicate the frequency in which the teachers engage in pedagogical practices that have proved to be related to better student learning in Mathematics. Finally, I am including in the analyses a set of dummy variables measuring student-teacher ratio (STDTEACHRATIO1-STDTEACHRATIO4), which can go from "less than 15 students in the classroom" to "41 or more students in the classroom". The omitted category is STDTEACHRATIO1.

5.2.2 Descriptive Statistics: Public and Private Schools

5.2.2.1 Peer Group Composition

The difference in peer-group composition between public and private schools are substantial, which means that a student attending a private school interacts with a student body of better quality that the one he or she can be in contact with in a public school. Table 17 presents the main differences in peer group composition variables.

In terms of student expectations, 90.6 percent of the students in private schools expect that in the future they will attain a college education or more, whereas only 65.5% of students in public schools expect to reach that academic level. The same happens with parental expectations. In private schools, 26.6 percent more parents than in public schools, expect higher levels of education from their children. In addition to that, the average score in the Parental Interest Index for public school is -0.02 versus the 0.27 score of private school, which is a little more that a quarter of a standard deviation, showing that students who attend private schools are more likely to interact with other children whose parents tend to be more interested in the education of their children than public student's parents, which would very likely translate in an advantageous educational environment for them.

As expected, there are also marked differences in the SES of students attending urban public schools and those attending private schools. In private schools, 74.70% of students have access to either public or private health services, whereas only 37.19% of students in public school do. In addition to that, public schools have a proportion of students who have computer at home more than twice as large as the corresponding proportion in public schools.

Table 17: Mean values for variables measuring Peer-Group Composition by Type of School

Variables	School Type Urban Public	 Private
Family Expectations and Educational Interests		
Percentage of Students in the school that their educational expectation is to attain a bachelor's degree or a graduate education (Studentexp_classper)	65.55	90.66
Percentage of students in the school whose parents expect them to attain either a bachelor's or a graduate education (Parentalexp_classper)	58.00	83.64
Average score in the index Parentalint of the students in the school (Parentalint_classper)	-0.02	0.27
Socio-Economic Status		
Percentage of students in the school whose family receive medical attention either at the IMSS, ISSSTE or similar institutions, or go to private clinics and private health services (Healthserv_classper)	37.19	74.70

…**Continuation Table 17**

Variables	**School Type** **Urban Public**	**Private**
Percentage of students within the school that work besides studying. (Work_classper)	18.36	12.09
Percentage of students within the school that have a computer at home (Computer_classper)	36.24	86.67
Percentage of students within the school that have a car at home (Car_classper)	58.32	91.75
Percentage of students in the school that have 100 or more books at home (Books_classper)	15.09	37.48
Percentage of students in the school whose mother's maximum level of schooling is college or beyond (Mothsch_classper)	9.28	51.86

Also, in private schools, on average, about 91.75% of students have cars, whereas in public schools that figure is only 58.32 percent. In terms of the percentage of students within the school that work besides studying, the difference between both types of school is only 6 percentage points. Also, in private schools, the percentage of students who have 100 books or more at home are 37.48 percent, more than double the figure of students who have those books in public schools (15.09%). In addition to that, half of the mothers of students in private schools have a college education or beyond, whereas only 9.28 percent of mothers with students in public schools have that level of education.

5.2.2.2 Predictor Variables

With respect to school characteristics, there are important differences between public and private schools in the four factors that are hypothesized to explain the public-private achievement differential: school's physical resources, school management, teacher quality, and teaching practices and classroom organization. In this section I present the basic descriptive statistics and discuss the most important differences.

Table 18 shows the mean values for variables measuring School Resources.

Table 18: Mean values for variables measuring School Resource by Types of School

	School Type	
	Urban Public	Private
School Physical Resources		
School Physical Resources Index (Schoolphysres)	-.2397	1.460
School Pedagogical Resources		
School Pedagogical Resources Index (Schoolpedres)	-.1274	1.022
School Computer Resources Index (Schoolcompres)	-.1027	.1103
Availability of Books at School Dummy System		
Schoolbooks1 = there are less than 100 books in the school	.10	.17
Schoolbooks2 = if there are between 100 and 200 books in the school	.15	.19
Schoolbooks3 = if there are between 200 and 400 books in the school	.25	.21
Schoolbooks4 = if there are more than 400 books in the school	.49	.43

It is clear that with the exception of the number of books available at the school, private school tend to be, on average, considerably more equipped than public schools in terms of infrastructure and pedagogical resources. Private schools scored, on average, 1.6 standard deviations more than their public counterparts in the physical resources index, which convey the availability of resources such as bathroom, sport facilities, library, and the like. Private schools also scored a little more than one standard deviation more than public schools in the pedagogical resources index, which means that private schools have on average considerable more pedagogical resources, such as computer projectors, television, and video recorder. In term of computer resources, private schools scored 20% of one standard deviation above public schools in the School Computer Resources Index. In terms of number of books available at the school, public schools are more equipped than private schools. In 49% of the public schools, the school principals informed that there were more than 400 books in the school, versus 43 percent of principals in private schools informing the same figure of books.

In terms of school management, Table 19 presents the descriptive statistics for the respective variables. There are some important differences in terms of the pedagogical environment and the general opportunities to learn available to students at public and private schools school. These features of the school management are typically regulated, or at least highly influenced, by school principals. The average value of the Principal Support Index is -0.13 for public schools, and 0.37 points for private schools. Since the index has a mean of 0 and a standard deviation of 1, this means that the difference in the Principal Support Index between these two types of schools is half of one standard deviation.

Table 19: Mean values for variables measuring School Management by Type of School

Variables	School Type Urban Public	Private
Teacher Collaborative Work		
Principalsupp = Principal Support Index	-0.13	0.37
Teachcollwork = Teacher Collaborative Work Index	-0.14	0.32
Curriculum Exposure		
Number of Class Days Lost in the Year Dummy System		
Classloss0 = There were no cancelled school days in the school year	0.10	0.30
Classloss1 = There were 5 or less cancelled school days in the school year	0.20	0.14
Classloss2 = There were between 6 and 10 cancelled school days in the school year	0.34	0.34
Classloss3 = There were between 11 and 20 cancelled school days in the school year	0.24	0.18
Classloss4 = There were more than 20 cancelled school days in the school year	0.11	0.05
Length of School day Dummy System (Schooldayhrs1- Schooldayhrs3)		
Schooldayhrs1 = The regular school day last 4.5 hours or less	0.37	0.01
Schooldayhrs2 = The regular school day last between 5 and 6 hours	0.61	0.62
Schooldayhrs3 = The regular school day last 6.5 hours or more	0.02	0.37

Therefore, the kind of support the teacher can receive in private school serving the poor is considerably higher than the one the teachers receive in public schools. Something similar happens with respect to the Teacher Collaborative Work Index, where there is a distance of almost half of a standard deviation in the index (an average -0.14 points for public schools and an average of 0.32 points for private schools), which clearly indicates that teachers in private school can draw more support and collaboration from their peers than their counterparts in public schools.

With respect to the management factors that determine the level of curriculum exposure that the students have at the school, there are also some drastic differences between the public and private schools. There are considerably more cancelled days in public schools than in private schools: 30 percent of the private school teachers that are part of this study indicated that there were no cancelled days in their schools during the year, compared with only 10 percent of the teachers in public schools. In addition to that, there were only 5 percent of teachers in private schools that informed that there were 20 or more cancelled days in the school year, against 11 percent of teachers in public schools who stated the same. This means that, from the basic perspective of the actual number of days that the students spend at school, private schools offer over the course of an academic year several more days of schooling. But not only that, there are also differences in the length of the school day between both types of schools. There are 37 percent of teachers who stated than in their public schools, the regular school lasted 4.5 hours or less, versus 1 percent of teachers in the private schools who informed that the school day lasted only that long. On the other side of the continuum, 37 percent of private schools appear to have school days that last 6.5 hours or more, versus only 2 percent of public schools with school days that long. Therefore, it seems that students have more opportunity to learn in private school than in public schools.

In terms of teacher quality, as in this case, is commonly measured with indicator of teacher education and teacher experience, there does not seem to be great differences between public and private school teachers. Table 20 conveys the mean value for the two system of variables used to measure teacher education and teacher experience.

Table 20: Mean values for variables measuring Teacher Quality by Type of School

Variables	School Type: Urban Public	School Type: Private
Teacher Education Dummy System		
Teachedu1b = Teacher education is high school or technical education	0.00	0.03
Teachedu 2n = Teacher education is “normal basica”	0.27	0.20
Teachedu 3ns = Teacher education is “normal superior” or college	0.61	0.57
Teachedu 4ol = Teacher education is non-educational bachelor	0.04	0.12
Teachedu 5g = Teacher education is graduate education	0.07	0.07
Teacher Experience Dummy System		
Teachexp1 = Teacher has two or less years of experience	0.08	0.10
Teachexp2 = Teacher has between 3 and 10 years of experience	0.23	0.39
Teachexp3 = Teacher has between 11 and 15 years of experience	0.09	0.17
Teachexp4 = Teacher has 16 or more years of experience	0.60	0.33

There are only small differences in the amount of education teachers have between these two types of schools, although in terms of experience, the teachers with more experience actually work in public schools. It is very likely that this is due to the fact that the public education system is much older and offers tenure to teachers, and that until very recent there were no private schools affordable to the poor in Mexico.

In terms of teacher practices and classroom organization it is clear that there are very different teaching dynamics going on in the classroom of public and private schools. Table 21 presents the mean value for all variables within this category.

Table 21: Mean values for variables measuring Teaching Practices and Classroom Organization by Type of School

Variables	School Type Urban Public	School Type Private
Good Pedagogy Index (Goodpedagogy)	-0.0735	0.3759
Math Pedagogy Index (Mathped)	-0.1032	0.3934
Math Pedagogy Resource and Collaborative Work Index (Mathpedrscollwk)	0.0507	-0.4905
<u>Amount of Curriculum Covered in the Academic Year Dummy System</u>		
Curricoverage1 = The curriculum's coverage was 50% or less	0.01	0.00
Curricoverage2 = The curriculum's coverage was 60 to 70%	0.14	0.03
Curricoverage3 = The curriculum's coverage was 80%	0.48	0.19
Curricoverage4 = The curriculum's coverage was 90 to 100%	0.37	0.78
<u>Student - Teacher Ration</u>		
Stdteachratio1 = Less than 15 students	0.05	0.19
Stdteachratio2 = Between 16 and 25 students	0.37	0.36
Stdteachratio3 = Between 26 and 40 students	0.54	0.35
Stdteachratio4 = 41 or more students	0.04	0.09

Although there were only small differences in Teacher Quality (education and experience) between public and private schools, there seem to be very large differences in terms of "*teaching* quality" between the two types of schools, which is referred to the quality of the actual teaching going on in the classroom. In the Good Pedagogy Index, teacher in private schools average almost 40 points more than teachers in private schools (40% of one standard deviation in the index). This means that when it comes to applying general good pedagogy practices, such as how to correct their students' mistakes or allow students to express their opinions, the educational practices of teachers in private schools are of more quality than those of public school teachers. This is true despite the fact that there does not seems to be a difference between both types of teachers in terms of education, or the fact public school teachers have on average more teaching experience.

A similar trend can be found by comparing the average results of Mathematics Pedagogy Index, the difference between public and private school teacher is even larger: half of one standard deviation in the Math Pedagogy Index. Therefore, poor students in private school are more likely to learn in a classroom where teachers put to practice more appropriate pedagogical techniques for the learning of Mathematics.

It is also clear, that in addition to be exposed to better teaching practices, students in private schools have more opportunity to learn than students in public schools. In private schools, 78 percent of the teachers considered that the in their classrooms the 6^{th} grade curriculum would be covered between 90% and 100% in the academic year. In public schools, that figure is only 37 percent. Therefore, students in private school seem to be exposed to a greater proportion of the 6^{th} grade curriculum. Considering that, as discussed above, the indicators of teaching quality are also considerably higher in private schools, poor students in these schools are exposed to almost the entire the 6^{th} grade curriculum, which is also delivered to them with better teaching quality.

In addition to differences in the actual teaching practices taking place in public and private schools, private schools also offer, on average, a smaller class size than public schools. In private schools, 55% of classes have less than 25 students, where in public schools this figure is 42%.

5.3 Empirical Results

5.3.1 Baseline Control Model and the Private School Differential

I fitted a group of nested regression models to control the effects in student achievement in Mathematics of background variables and peer group composition. In this way, the remaining effect of Private School would reflect the effect of the differentiated school factors focus of this research, net of any personal characteristics or peer-group effect. Table 22 presents the results.

Model 0 shows the raw effect of Private School in achievement in mathematics. Without taking into consideration any other factor, attending a private school is associated to an average difference of almost 80% of a standard deviation of the mathematics test. However, as it was largely discussed while answering to my first research question, this raw comparison between public and private school is biased and should not be considered for any practical purpose.

Model 1 controls for self-selection into private school and, therefore, the magnitude and direction of the coefficient that conveys the private school effect is close to the earlier estimations for my first research question. On the other hand, it is also clear that if I add to Model 0 the variables controlling for school peer-group composition, the perspective is also very different. Model 2 shows that once I control for peer-group variables, the Private School effect goes down to 24.29 test points only. Moreover, when I included in the model both the Propensity Score variable and the peer group variables, the Private School effect is only 19.68 points.

Table 22: Series of Nested Regression Models aimed at building a Control Model to estimate the effect of Private School on student achievement in Mathematics, controlling for Self Selection into Education Sector (Propensity Score) and Peer Group Effects, with poverty region fixed effects.

Variables	Model 0 (N=3,311)		Model 1 (N=2,954)		Model 2 (N=3,311)		Model 3 (N=2,954)	
Private School	78.13	****	42.53	****	24.29	****	19.68	**
Propensity Score			89.07	****			48.54	****
Peer Group Effects								
% Students expectation of bachelor's degree					-0.25		-0.18	
% Parental expectation of bachelor's degree					0.76	****	0.72	****
Average of Parental Interest Index					26.31	****	28.66	****
% Students with medical attention					0.14		0.09	
% Students that works					-0.83	****	-0.80	****
% Students with computer at home					-0.09		-0.06	
% Student with car at home					0.21	**	0.13	
% Students with 100 books at home					-0.23		-0.32	*
% Students with mother with college degree					0.66	****	0.39	**
Constant	493.29	****	489.07	****	464.63	****	469.05	****
R-squared	0.069		0.091		0.137		0.142	

*p<.10 **p<.05 ***p<.01 ****p<.001

This means that the private school effect in the mathematic achievement of poor students that can be theoretically attributed to differences in the school inputs studied in this research is only a fifth of a standard deviation in the Mathematics test. This means that out of the original Private School Effect of 42.53 points, reported in Model 1, 22.85 points (or 54% of this original effect) is attributable, on average, to the quality of the peer group that the student has the opportunity to interact with at the private school. This is a very important effect, which is consistent to other findings in the literature (Harris, 2010). The fact that peer group composition has not been the object of any public educational policy in Mexico does not change the fact that peer group effects alone account for little over half the private school advantage, once student background is taking into account. It is worth noticing that recent literature has challenged the idea that race, ethnicity or even income (which is proxied in this dissertation's analyses) have any substantial effect on achievement once researchers properly account for peer's achievement (Hoxby & Weingarth, 2005). I do not have available measures of peer's achievement or even direct measures of income to properly address this argument. Therefore, this finding is not robust and should not be taken at face value.

The variables accounting for peer-group composition are statistically significant and bear much weight in academic achievement. For example, a standard deviation difference in the index that conveys the level of parental interest in the education of their children is associated to an average of 28.66 test points in mathematics, which is more than a quarter of a standard deviation in the mathematics test. Almost all variables that reflect peer-group composition are statistically significant and are of considerable magnitude.

As stated earlier, peer-group composition has not really be the subject of public policy in Mexico, at least not at large scale, and therefore I decided to include it in the control model to control its effect and be able in that way to identify the effects of school inputs subject of modification through policy change.

From the perspective of a parent who is choosing a school that best serves his or her child, it may not matter whether a private school is better for their child because it possesses good teachers and strong curricula of because it attracts students who form an academically supportive peer group. However, from the perspective of public policy makers, it does matter. The reason is that not all schools can serve students from families that provide "above-average" support for academic achievement. Therefore, if it is true that peer group composition is relevant to student achievement, it is also true that it is a resource that is scarce, and policy makers need to take this into account. The potential benefits of peers might vanish as the number of private school increases. Nonetheless, public policy could limit the extent to which schools segregate students into homogenous groups. This has happened in fact in Chile, where over the last few years there have been intentional attempts to prevent schools from segregating students through policy (Valenzuela, Bellei, & de los Ríos, 2013).

5.3.2 The Role of School Factors in Explaining the Private School Advantage in Mathematics

I introduced in the baseline model the variables related to school physical resources and school management. Table 23 shows the results. Model 4 shows that once the variables related to school physical resources are taken into account in the model, in addition to the variables included in the baseline model, the private school effect diminishes even further from the effect depicted in Model 3 (19.68 points). Now the achievement differential attributed to being enrolled in a poor school is, on average, only 17.86 test points. On the other hand, school management also seems to diminish the effect of attending a private school even a little more. Model 5 shows that taking into account differences in school management decreases the effect of private school, on average, to 15.27 tests points (15% of a standard deviation). In addition to that, the private school effect is now barely significant at the 0.10 level.

Table 23: Series of Regression Models that Predict the Effect of Private School on student achievement in Mathematics, controlling for the effect of Physical Resources and School Management, and the variables included in the Control Model, with poverty region fixed effects.

Variables	Model 4 (N=2,676)		Model 5 (N=2,837)	
Private School	17.86	**	15.27	*
School Physical Resources				
School Physical Resources Index	3.57			
School Pedagogical Resources Index	1.73			
School Computer Resources Index	-1.34			
Availability of Books at School				
Between 100 and 200 books	-12.58			
Between 200 and 400 books	3.36	*		
More 400 books	1.58			
School Management				
Principal Support Index			1.28	
Teacher Collaborative Work Index			-1.18	
Number of Class Days Lost				
5 or Less			-2.02	
Between 6 and 10			-8.99	
Between 11 and 20			-6.67	
More than 20			-8.37	
Length of School Day				
Between 5 and 5 hours			2.21	
6.5 hours or more			16.19	*
CONTROL MODEL				
Propensity Score	45.76	****	50.55	****
Peer Group Effects				
% Students expectation of bachelor's degree	-0.11		-0.14	
% Parental expectation of bachelor's degree	0.62	****	0.67	****
Average of Parental Interest Index	25.91	****	27.23	****
% Students with medical attention	0.14		0.11	
% Students that works	-0.82	****	-0.77	****
% Students with computer at home	-0.09		-0.08	
% Student with car at home	0.07		0.15	
% Students with 100 books at home	-0.36	**	-0.29	*
% Students with mother with college degree	0.40	**	0.36	**
Constant	474.98	****	471.30	****
R-squared	0.147		0.150	

*p<.10 **p<.05 ***p<.01 ****p<.001

In Table 24 I show the private school effect on student achievement on mathematics after introducing into the baseline model the last two school factors: teacher quality (Model 6) and teaching practices and classroom organization (Model 7).

Table 24: Series of Regression Models that Predict the Effect of Private School on student achievement in Mathematics, controlling for the effect of Teacher Quality and Teaching Practices and Classroom Organization, and the variables included in the Control Model, with poverty region fixed effects.

Variables	Model 6 (N=2,923)		Model 7 (N=2,746)	
Private School	19.46	**	26.97	***
Teacher Quality				
Teacher Education				
"Normal Basica"	-47.19	**		
College	-40.30	**		
Non-educational Bachelor	-45.40	**		
Graduate School	-43.56	**		
Teacher Experience				
Between 3 and 10 years	1.41			
Between 11 and 15 years	-4.87			
16 or more years	3.45			
Teaching Practices and Classroom Organization				
Curriculum Coverage				
60% to 70%			28.48	
80%			24.05	
90% to 100%			31.06	*
Good Pedagogy Index			16.76	****
Math Pedagogy Index			2.20	
Math Pedagogy Resource Index			5.54	****
Student-Teacher Ratio				
Between 16 and 25 students			5.30	
Between 26 and 40 students			15.68	**
41 or more students			6.17	
CONTROL MODEL				
Propensity Score	47.57	****	44.77	****
Peer Group Effects				
% Students expectation of bachelor's degree	-0.17		-0.28	
% Parental expectation of bachelor's degree	0.72	****	0.69	****
Average of Parental Interest Index	29.10	****	20.73	***
% Students with medical attention	0.10		0.04	
% Students that works	-0.74	****	-0.75	****
% Students with computer at home	-0.08		-0.11	
% Student with car at home	0.15		0.11	
% Students with 100 books at home	-0.30	*	-0.38	**
% Students with mother with college degree	0.39	**	0.39	**
Constant	507.33	****	445.40	****
R-squared	0.145		0.187	

*p<.10 **p<.05 ***p<.01 ****p<.001

Teacher quality, as measured by teacher education and teacher experience, does not explain any part of the private school advantage. The coefficient of private school in Model 6 is 19.46 test points, practically the same than what it was in the baseline model (19.68 test points). Although there is an effect of teacher quality in student achievement, this effect does not seem to be a differentiated effect linked to private schooling.

On the other hand, once I added to the baseline control model, the group of variables associated to teacher practices and classroom organization, the effect of private actually increased. It went from 19.68 test points (Model 3) to 26.97 test points (Model 7), a little more than a quarter of a standard deviation, accentuating in this way the private school effect.

5.3.3 Results and Discussion: The Combined Effect of School Factors and the Private School Effect

It is important to assess how these school factors behave together in the same model and if in that case, there is still a private school effect left that remain unexplained. Table 25 reports the final model.

After taking into consideration the baseline control model, and the variables associated to physical resources, school management, teacher quality, and teaching practices and classroom organization, the differentiated effect of private school became small and not significant. This means that, as originally hypothesized, the private school effect, net of family background and peer-group effects, reported in Model 3, were explained away by the school factors included in the final model.

In other words, there is no remaining private school advantage in mathematics for the poor if differences between public and private school in the educational factors considered in this research are resolved, net of peer-group effects. According to findings reported in section 5.3.1, the peer-group effects were very large; they accounted for about half of the private school advantage. The rest of the school inputs together, account for the rest of the private school advantage.

Table 25: Final Models estimated to predict the effect of Private School on student achievement in Mathematics, controlling for the effect of physical resources, school management, teacher quality, and teaching practices and classroom organization, with poverty region fixed effects.

Variables	Model 8 (N=2,391)	
Private School	16.92	
School Physical Resources		
School Physical Resources Index	4.35	*
School Pedagogical Resources Index	0.02	
School Computer Resources Index	-0.46	
Availability of Books at School		
Between 100 and 200 books	-11.36	
Between 200 and 400 books	3.84	
More 400 books	-0.10	
School Management		
Principal Support Index	-0.62	
Teacher Collaborative Work Index	-0.61	
Number of Class Days Lost		
5 or Less	-2.65	
Between 6 and 10	-8.26	
Between 11 and 20	-3.12	
More than 20	-6.08	
Length of School Day		
Between 5 and 5 hours	5.01	
6.5 hours or more	19.82	**
Teacher Quality		
Teacher Education		
“Normal Basica”	-44.01	**
College	-41.88	**
Non-educational Bachelor	-51.03	**
Graduate School	-45.35	**

*p<.10 **p<.05 ***p<.01 ****p<.001

…Continuation Table 25

Variables	Model 8 (N=2,391)	
Teacher Experience		
Between 3 and 10 years	3.00	
Between 11 and 15 years	-0.12	
16 or more years	1.66	
Teaching Practices and Classroom Organization		
Curriculum Coverage		
60% to 70%	23.22	
80%	16.55	
90% to 100%	24.23	
Good Pedagogy Index	16.97	****
Math Pedagogy Index	2.72	
Math Pedagogy Resource Index	6.25	****
Student-Teacher Ratio		
Between 16 and 25 students	7.02	
Between 26 and 40 students	17.55	**
41 or more students	7.83	
CONTROL MODEL		
Propensity Score	43.59	****
Peer Group Effects		
% Students expectation of bachelor's degree	-0.17	
% Parental expectation of bachelor's degree	0.57	***
Average of Parental Interest Index	19.27	***
% Students with medical attention	0.08	
% Students that works	-0.66	****
% Students with computer at home	-0.14	
% Student with car at home	0.11	
% Students with 100 books at home	-0.40	**
% Students with mother with college degree	0.40	**
Constant	493.17	**
R-squared	0.203	

*p<.10 **p<.05 ***p<.01 ****p<.001

Of some importance is to analyze the individual effect that each school factor has in mathematics achievement. This exercise would help us understand the factors associated to the academic performance of the poor, information that can be of use for policy analysis and for the understanding of academic achievement at the end of Mexican SES distribution. This particular analysis will also shed light into the means that help private schools make a difference for the achievement of the poor.

First, according to Model 8, only one of the indexes that account for the effect of the school physical resource in achievement is barely statistically significant, controlling for all other variables included in the model. A one standard deviation increase in the index of physical resources is only associated to an average increase of 4.35 test points in Mathematic. This seems to be consistent with the literature that tends to confirm that physical resources contribution to achievement in general is marginal. School pedagogical resources and school computer resources do not seem to have any impact at all. The dummy system of books availability, a proxy for other pedagogical resources, is also not significant.

In terms of school management, the environment and educational setting created in the school by the principal seem to be only of relative importance. The support the teachers receive from the principal and the amount of collaboration they receive from their peers does not seem to be a factor in student achievement. The Principal Support Index and the Teacher Collaborative Work Index are not statistically significant in Model 8. The same happens with the number of class days lost during the academic year. The entire dummy system reflecting this factor is not statistically significant. On the other hand, the length of the school day bears some weight on student mathematic achievement. On average, students who attend schools with shifts of 6.5 hours or more, tend to outperform their peers, all things being equal, by almost a fifth of a standard deviation.

Teacher quality (understood as the level of teacher education and experience) presents very mixed results. This is consistent with the literature review: in general, teacher quality does not seem to provide a clear pattern of influence into educational achievement. For example, with respect to teacher education, the analysis produced counter-intuitive results. Having teachers with more education seems to be, on average, negatively associated to student achievement. This is true to the extent that having teachers in the school with graduate studies is associated with a decrease in Mathematics test of 45 points on average, only 5 points short of half of a standard deviation in the mathematics test. Evidently, this does not imply that more education actually hurts student achievement. It is clear that this variable is picking up other associated effects. For example, the vast majority of more educated and experience teachers –measured in a traditional way- tend to work in the Public education system. Therefore, is quite possible that Teacher Education is picking up other non-measured factors of the public education system. It is clear, that in particular with this subject matter, there are some negative correlation between the education of the teachers and other school factors that are affecting achievement negatively.

With respect to the teaching practices and classroom organization, the quality of pedagogy practiced in the classroom is of the highest importance. The Good Pedagogy Index is positively associated with achievement. An increase of one standard deviation in this index is associated with an average increase of 17 points in Mathematics. However, out of the two indexes that reflect the quality of pedagogy in mathematics, one is not statistically significant (Math Pedagogy Index) and the other –Math Pedagogy Resource

Index- has only a marginal effect: a difference of 6.25 points for a difference of 1 standard deviation in the index.

On the other hand, student-teacher ratio presents contradictory results. According to Model 8, students who attend a classroom that have between 26 and 40 students, as opposed to less than 15 students, tend to perform better, on average, by almost 18 test points.

There is no clear explanation in the context of this research that would explain why students learn better in a larger classroom. Considering that most larger classroom are actually in public schools, it is my contention that the student-teacher ratio variables is picking some other effect that is going on in the public schools. For example, is very likely that more capable teachers are actually placed in larger classrooms, this would explain the achievement premium associated to larger groups. This is a hypothesis that should be tested in future studies.

Finally, one important thing to keep in mind is the fact that some of the proxies of quality and pedagogy used in these analyses are rather crude, and they probably fail to capture very important aspects of teacher quality. For instance, teacher education and qualifications fail to account for the wide variation in quality among the different institutions where teachers are educated. In other words, before drawing definitive conclusions about the role that teacher quality, teaching practices, and classroom organization have on explaining the private school advantage, more research with better specification of these variables should be conducted.

6. Conclusions

Mexico is a country where there are no policies to promote enrollment in private schools, either on the demand-side or on the supply-side of the market. Nonetheless, there seem to be indications that at least a proportion of the poor are looking for private education alternatives in elementary education. In this dissertation, I used information of math achievement from poor students (students beneficiaries of the *Oportunidades* program) attending public and private school participants of the EXCALE06-2009, I found that private schools in Mexico offer a clear advantage for poor students in primary education. Poor students in private schools outperformed poor public school students by 48 test points (or 0.48 standard deviations) in Mathematics.

Descriptive statistics show that students attending private schools are relatively more advantaged than those attending public schools, probably as a result of selection bias. The private school advantage was therefore identified after successfully correcting for selection bias using propensity score matching. The results passed different robustness checks: they are robust to the use of different matching estimators, they are robust to hidden bias arises from the geographic location of schools, and it has been demonstrated that a hidden bias would need to increase the odds of entering into a private school by 90% to actually affect the estimation of the private school advantage.

The 0.48 sd private school effect found in this dissertation is indeed very large compared to most of existing literature. These large results might have to do in part with the fact that this research is focusing on poor students attending private urban schools, which is the right counterfactual to use. Also, large results might be also attributed to the fact that all students in the sample attending private schools are all beneficiaries of

Oportunidades, and that some components of *Oportundiades* might be positively interacting with private schooling to produce these large effects. In addition to that, exposing poor children to stronger peers seems to contribute in great part to the size of the private school effects.

All of the remaining private school effect is accounted for by identifiable school factor, including peer-group composition and the four factors hypothesized in the research questions. Once I have taken into account student-self selection into private school and peer-group composition (included in the baseline model), and the variables associated to physical resources, school management, teacher quality, and teaching practices and classroom organization, the differentiated effect of private school became small and not significant. This means that all the original effect of studying in a private school was captured by actual differences in identifiable school factors, most of which have been the focus of educational policy in Mexico in the past years.

Special consideration should be given to the role of peer-group variables. A very important part of the original private school effect (54%) is explained by the peer-group composition of private schools. Poor students that attend private schools are exposed to peers whose parents are more concerned about their education and, in general, expect more about their academic achievement and attainment; their families have more education resources, and better socioeconomic status. It is very likely that parents might be attracted to private schools so their children are exposed to better peers; an expectation that in this situation proved to be supported by the data.

Nonetheless, some of the variables used to account for peer-group effects are not very commonly used in the literature and represent a rather indirect ways to measure peer characteristics. Therefore, this limitation should be taken into account while interpreting the results. However, the quality of peer group is a scarce school factor, not easily manipulated by public policy and definitely not easy to replicate at a large scale. Also, some of the measures used to account for teacher quality and pedagogy in the analyses aimed at identifying the determinants of private school advantage, have important limitations and, probably, fail to capture very important aspects of these dimensions.

Results can have important policy implication on all sides of the policy spectrum. It can be argued that the difference in serving the poor by private education are so large, than rather than dealing with the public school system, financial and pedagogical efforts should be directed to facilitate the access of the poor to this kind of school. On the one hand, the main findings of this study show that all of the factors that explain the private school differential can be affected by public policy through a variety of programs. Therefore, public schools, given the right policies, can do a considerably better job in educating the poor than the one they are doing right now.

This is the first study of its type. It takes advantage of an oversampling of private schools in the INEE test exercise and it represents the first attempt at understanding the performance of the poor in private schools. Propensity score matching is an identification strategy that has limitations. Even though the results hold to different matching algorithm and sensitivity bias analyses, the results do not have the benefits of a random experiment or other identification strategies that are more robust to hidden bias. The reader must exercise caution in drawing policy conclusions from the present research.

However, this research has identified some potentially important patterns related to achievement in private schools. Further analyses using modern methods for bias reduction, as well as better data sources for studying the effects of school factors, family factors and student factors will lead to better understanding of these complicated systems, and these studies will help us develop new policies and ideas for improving both public and private schools, and ultimately offer better educational opportunities for poor children in Mexico.

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Appendix

Table A1: Variable Definitions

Variable	Description
	Panel A: Outcome Variable
MATH	Student's performance in a Math test.
	Panel B: Propensity Score-Matching Predictors
Student Characteristics	
FEMALE	Dummy variable indicating whether the student is female.
AGE	Student's age in years.
PRESCH	Dummy variable indicating whether the student went to preschool.
LANG1-LANG3	Three dummy variables indicating the predominant language spoken at home by the student: LANG1 (Spanish), LANG2 (Indigenous), LANG3 (Other). Omitted category: LANG1.
Socioeconomic Status	
MOTHSCH1- MOTHSCH6	Seven dummy variables indicating years of schooling of the student's mother, ranging from no formal education at all (MOTHSCH1) to graduate studies (MOTHSCH6). Omitted category: MOTHSCH1.
FATHSCH1- FATHSCH6	Seven dummy variables indicating years of schooling of the student's father, ranging from no formal education at all (FATHSCH1) to graduate studies (FATHSCH6). Omitted category: FATHSCH1.
BOOKS0-BOOKS5	Four dummy variables indicating the number of books available at home ranging from none (BOOKS0) to 200 and more (BOOKS4). Omitted category: BOOKS0.
HEALTHSERV0-HEALTHSERV3	Four dummy variables indicating family access to health services, ranging from no access to any kind of services (HEALTHSERV0) to access to private health services (HEALTHSERV3).
COMPUTER	A dummy variable indicating whether there is a computer at home
CAR	A dummy variable indicating whether there is a car at home
TELEPHONE	A dummy variable indicating whether there is telephone at home
	Panel C: Question Predictors
PRIVATE	Dummy variable indicating whether the student attends a private school.
Physical Resources	
SCHOOLPHYSRES	Index measuring the level of physical resources of school. It has mean of 0 and an sd of 1
SCHOOLPEDRES	Index measuring the pedagogical resources of school. It has mean of 0 and an sd of 1
SCHOOLCOMPRES	Index measuring the level of computer and electronic resources of school. It has mean of 0 and an sd of 1
SCHOOLBOOKS1-SCHOOLBOOKS4	Four dummy variables indicating the number of books available at school ranging from 100 or less (SCHOOLBOOKS1) to 400 and more (SCHOOLBOOKS4). Omitted category: SCHOOLBOOKS1
School Management	
PRINCIPALSUPP	Index measuring the level to which principal provide support to the teachers in the school. It has mean of 0 and an sd of 1
TEACHCOLLWORK	Index measuring the collaborative relationship between teachers in the school. It has mean of 0 and an sd of 1
CLASSLOSS0-CLASSLOSS4	System of dummy variables indicating the number of classes cancelled during the academic year at the school for any reason, ranging from none (CLASSLOSS0) to 20 or more (CLASSLOSS4).

…**Continuation Table A1**

Variable	Description
	Panel C: Question Predictors
SCHOOLDAYHRS1-SCHOOLDAYHRS3	System of dummy variables indicating the actual length of the school day in terms of hours, which, ranging from 4.5 hours or less (SCHOOLDAYHRS1) to 6.5 hours or more (SCHOOLDAYHRS3). The omitted category is SCHOOLDAYHRS1
Teacher Quality	
TCHEDU1B- TCHEDU5G	System of dummy variables indicating the educational attainment of the student's teacher, ranging from high school or less (TCHEDU1) to graduate studies (TCHEDU5G). The omitted category is TCHEDU1B.
TEACHEXP1- TEACHEXP4	System of dummy variables indicating the level of educational experience of teachers, ranging from two or less (TEACHEXP1) to 16 or more (TEACHEXP4). The omitted category is TCHEDU1B.
Teaching Practices and Classroom Organization	
CURRICOVERAGE1-CURRICUVOERAGE4	System of dummy variables measuring the amount of curriculum the teacher expects to cover during the academic year, ranging from 50% or less of the academic curriculum (CURRICOVERAGE1) to 100% (CURRICUVOERAGE4). The omitted category is CURRICUVOERAGE1
GOODPEDAGOGY	Encompasses the frequency in which teachers practice sound general pedagogical practices. It has mean of 0 and an sd of 1
MATHPED	Index depicting the frequency in which the teachers engage in pedagogical practices that have proved to be related to better student learning in Mathematics. It has mean of 0 and an sd of 1
MATHPEDRSCOLLWK	Index depicting the frequency in which the teachers engage in pedagogical practices that have proved to be related to better student learning in Mathematics. It has mean of 0 and an sd of 1
STDTEACHRATIO1-STDTEACHRATIO4	set of dummy variables measuring student-teacher ratio, ranging from "less than 15 students in the classroom" (STDTEACHRATIO1) to "41 or more students in the classroom" (STDTEACHRATIO4). The omitted category is STDTEACHRATIO1

Table A2: Summary of Logistic Regression Analysis for the Prediction of *Oportunidades* Students' Enrollment into Private School, for Mathematics test taker's in the EXCALE06-2009, Controlling for Background Variables and state poverty level in a Multilevel Model. (N=2,954)

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Student-Level Variable						
Female	0.60	0.65	0.92	0.360	-0.68	1.87
Age in years	0.09	0.61	0.15	0.878	-1.10	1.28
Preschool	-1.05	2.33	-0.45	0.651	-5.63	3.52
Language spoken at home						
Indigenous	3.17	6.43	0.49	0.622	-9.42	15.76
Other language	0.46	2.06	0.22	0.824	-3.58	4.50
Mother's Education						
Primary school	0.91	3.21	0.28	0.778	-5.39	7.21
Secondary school	1.17	3.18	0.37	0.713	-5.07	7.41
High school	1.48	3.22	0.46	0.647	-4.84	7.79
College	2.64	3.25	0.81	0.415	-3.72	9.00
Graduate school	3.18	3.45	0.92	0.357	-3.59	9.95
Father's Education						
Primary school	1.48	2.28	0.65	0.518	-3.00	5.95
Secondary school	0.56	2.17	0.26	0.796	-3.70	4.82
High school	1.01	2.20	0.46	0.646	-3.30	5.32
College	3.98	2.27	1.75	0.080	-0.47	8.42
Graduate school	2.28	2.38	0.96	0.338	-2.38	6.93
Availability of Books at Home						
Around 10 books	3.56	1.75	2.04	0.041	0.14	6.99
Around 25 Books	4.41	1.78	2.48	0.013	0.93	7.90
Around 50 books	3.57	1.76	2.03	0.042	0.13	7.02
Around 100 books	3.84	1.78	2.16	0.031	0.35	7.34
Around 200 books	4.28	1.84	2.32	0.020	0.67	7.89
Health Services Available to the Family						
Family goes to popular or public clinic, or to a pharmacy	0.21	1.65	0.13	0.898	-3.03	3.45
Family goes to IMSS, ISSSTE or similar institution	0.50	1.64	0.30	0.762	-2.71	3.70
Family goes to private clinics and private health services	2.74	1.78	1.54	0.123	-0.75	6.23
Computer at home	1.82	0.87	2.09	0.037	0.11	3.53
Car at home	0.96	0.97	0.99	0.321	-0.94	2.86
Telephone at home	0.47	0.91	0.52	0.603	-1.31	2.25
State-Level Variable						
Poverty	0.23	0.19	1.25	0.211	-0.13	0.60

…**Continuation Table A2**

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Interaction Terms						
FemaleXPoverty	-0.01	0.01	-0.63	0.526	-0.04	0.02
AgeXPoverty	-0.01	0.01	-0.98	0.329	-0.04	0.01
PreschXPoverty	0.06	0.06	0.97	0.331	-0.06	0.18
LANG2IXPoverty	-0.10	0.18	-0.56	0.573	-0.45	0.25
LANG3OXPoverty	-0.01	0.05	-0.27	0.786	-0.10	0.08
Mothsch2pXPoverty	-0.01	0.06	-0.13	0.894	-0.13	0.11
Mothsch3sXPoverty	-0.01	0.06	-0.17	0.868	-0.13	0.11
Mothsch4hXPoverty	0.00	0.06	-0.07	0.943	-0.13	0.12
Mothsch5cXPoverty	-0.01	0.06	-0.19	0.847	-0.14	0.11
Mothsch6gXPoverty	-0.03	0.07	-0.40	0.686	-0.16	0.11
Fathsch2pXPoverty	-0.05	0.05	-1.09	0.277	-0.14	0.04
Fathsch3sXPoverty	-0.03	0.04	-0.63	0.530	-0.11	0.06
Fathsch4hXPoverty	-0.03	0.04	-0.61	0.545	-0.11	0.06
Fathsch5cXPoverty	-0.08	0.05	-1.78	0.075	-0.17	0.01
Fathsch6gXPoverty	-0.04	0.05	-0.80	0.426	-0.13	0.06
Books1XPoverty	-0.06	0.03	-1.79	0.074	-0.13	0.01
Books2XPoverty	-0.08	0.04	-2.16	0.031	-0.15	-0.01
Books3XPoverty	-0.06	0.04	-1.71	0.086	-0.13	0.01
Books4XPoverty	-0.05	0.04	-1.48	0.139	-0.12	0.02
Books5XPoverty	-0.07	0.04	-1.77	0.077	-0.14	0.01
Healthserv1XPoverty	-0.02	0.04	-0.55	0.585	-0.09	0.05
Healthserv2XPoverty	-0.02	0.04	-0.46	0.643	-0.09	0.05
Healthserv3XPoverty	-0.04	0.04	-1.01	0.312	-0.12	0.04
ComputerXPoverty	-0.02	0.02	-1.10	0.270	-0.06	0.02
CarXPoverty	-0.01	0.02	-0.37	0.713	-0.05	0.03
TelephoneXPoverty	0.00	0.02	0.09	0.931	-0.04	0.04
Intercept	-11.48	8.53	-1.35	0.178	-28.20	5.24

Log Likelihood	-575.7
Wald chi2 (53)	402.02
Prob > chi2	0.0000

VITA

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